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Development of a pragmatic multidisciplinary protocol to validate a contactless fall detection system for older adults in long-term care facilities

Chang-Chun Chen[1], Alisha H. Johnson[2], Marjorie Skubic[3], and Shu-Fen Wung[4]

Abstract

Background: Falls among residents of long-term care facilities are associated with substantial morbidity, mortality, and healthcare utilization. Despite the availability of numerous fall detection technologies, practical protocols for evaluating performance in real-world care environments remain limited. **Objective:** To develop a pragmatic and replicable protocol for validating contactless fall detection systems in long-term care environments. **Methods:** This article presents a protocol that combines structured testing by trained stunt actors, continuous real-world monitoring, and predefined procedures for event verification and classification to evaluate system performance across fall and non-fall events relevant to older adults. **Protocol description:** The protocol consists of three phases: pre-implementation assessment, system implementation and training, and system verification. It incorporates site assessment, sensor deployment, scripted testing, continuous monitoring, event verification, and predefined analytical procedures under real-world conditions. **Conclusion:** This protocol provides an approach for evaluating contactless fall detection systems in long-term care environments. Future studies are needed to apply the protocol across different sensor platforms and care settings to evaluate reproducibility, generalizability, and operational feasibility.

Keywords

falls, long-term care, older adults, sensor, validation protocol

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Introduction

Each year, up to 50% of residents in long-term care facilities (LTCFs) suffer falls, which are a primary contributor to increased morbidity and mortality.[1] For older adults residing in LTCFs, falls represent a serious safety hazard due to various factors, including multiple comorbidities, frailty, cognitive impairments, polypharmacy, vision changes, wandering tendencies, and decreased functional abilities.[2] Such incidents result in approximately three million emergency department visits and one million hospitalizations annually.[3] Falls also impose a substantial burden on the US healthcare system,

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accounting for approximately $50 billion in medical costs related to nonfatal fall injuries in 2015 and $754 million for fatal falls.[4,5]

Cognitive dysfunction associated with the progression of dementia can reduce an individual's ability to engage in activities of daily living, thereby increasing the risk of falls and subsequent injuries.[6] Falls can contribute to functional decline in older adults through injury, chronic pain, reduced mobility, increasing frailty, and fear of future falls.[7] This fear can lead older adults to avoid situations perceived to increase fall risk, such as slippery, sloped, or uneven surfaces and crowded environments, thus restricting their activities and reducing their quality of life.[8] Fear of falling, helplessness, and social isolation following a fall may increase interest in technologies designed to support safety monitoring.[9] An increasing number of older adults are comfortable using various personal monitoring technologies, such as fitness trackers, videoconferencing devices, personalized alerts, smartphones, and sensor-based monitoring systems for daily living and health self-management.[10] Older adults frequently identify maintaining independence as a key factor influencing their acceptance of health monitoring technologies.[10,11]

Current fall detection technologies

Current monitoring systems are designed to improve the quality of life for older adults by enabling them to self-manage health conditions through physiological monitoring or by providing assistance with everyday tasks, such as dressing. These systems also support caregivers in home and institutional settings by facilitating health management and promoting older adults' independence through safety monitoring and alert notifications.[12–14] Existing monitoring technologies encompass a broad range of modalities, including contactless environmental sensors, such as vision-based systems (e.g., RGB and depth sensors), radar systems, and ambient pressure sensors, as well as wearable devices such as pendants and wrist-worn trackers. Monitoring systems may also incorporate reminder applications and other hybrid functions related to safety, mobility, cognition, and disease self-management.[12,13,15,16] These developments align with recent advances in artificial intelligence (AI) and Internet of Things (IoT) technologies, facilitating continuous monitoring and supporting more adaptive and context-aware fall detection approaches.[17]

Recent literature has demonstrated that fall detection systems can be broadly classified into four categories: wearable, vision-based, ambient, and multimodal approaches. These approaches are often combined with analytical methods such as threshold-based techniques, machine learning, and deep learning algorithms.[18] Although these approaches have improved detection capabilities, they have also introduced variability in system design, sensor configurations, and data-processing pipelines.

Currently, most systems focus on individuals with mild cognitive impairment rather than those with more advanced stages of dementia, even though the latter population may particularly benefit from continuous monitoring technologies.[14] Although some systems leverage AI to enhance predictive capabilities using large datasets, they still require human interpretation and response, thereby increasing the cognitive burden on users and caregivers.[14] Furthermore, older adults and their caregivers often express concerns regarding wearable devices because of the burden associated with their use. This burden includes remembering when to wear devices, keeping track of them, avoiding loss, and maintaining charging schedules, all of which may reduce their usefulness.[14,19] In general, both formal and informal caregivers prefer unobtrusive technologies over wearable devices, provided that these technologies reduce caregiver burden and minimize the need for interpretation by delivering meaningful alerts.[19] Despite the growing adoption of contactless and multimodal systems, many existing approaches have been evaluated using limited or simulated datasets and lack consistent validation methodologies.[20,21]

Perceptions of fall detection technology among older adults

A large proportion of older adults place a high value on maintaining their independence and autonomy and actively seek to avoid negative stereotypes associated with aging, such as frailty and cognitive decline.[11] Research indicates that many older adults view fall detection devices as stigmatizing because their use may be perceived as signaling a loss of independence, thus diminishing interest in these technologies.[9] Additionally, concerns regarding costs and privacy may contribute to hesitancy toward adoption.[22] In contrast, surveys suggest that older adults and their families generally view monitoring technologies favorably when they are perceived as supporting independent living.[10,22] Users are primarily concerned with the practicality, security, and effectiveness of these systems in providing tangible benefits.[10,23] Consequently, some degree of intrusion may be considered acceptable when the technology is perceived to improve safety and health outcomes.[20,24,25]

These considerations present important challenges for the development and adoption of fall monitoring technologies among high-risk older adults. Such technologies must enhance safety while preserving privacy and supporting independence. According to the American Association of Retired Persons (AARP), more than 90% of older adults prefer to "age in place," reflecting a desire to remain in their homes and communities.[26] Fall detection technologies may support aging in place by providing additional safety monitoring while minimizing disruption to daily activities.[13,27] Features such as automated alerts and assistance-seeking functions may influence technology acceptance among some users.[10] Establishing the reliability and accuracy of these technologies is also important for fostering trust. In particular, minimizing false alarms is critical for reducing alarm fatigue, which can undermine user confidence.[28] Improved reliability may promote sustained use by increasing perceived usefulness and trust.[29]

Limitations of current methodologies

Research on fall monitoring technologies has predominantly relied on methodologies that do not accurately reflect real-world conditions and are often confined to controlled laboratory settings. For example, testing environments may lack furniture, be limited to a single-room design, and fail to accommodate multiple individuals in the same space.[30] Studies conducted under these conditions often include small samples, limited diversity in body characteristics, and a restricted range of movement activities.[30] Although multiple datasets are available for refining fall detection algorithms, most fall data are derived from young, healthy adults whose movement patterns differ substantially from those of older adults.[31–33] This reliance on simulated data, combined with the limited availability of real-world fall events, reduces the ecological validity and clinical relevance of existing datasets for frail older adults.[18,20]

To address these limitations, the protocol incorporates a systematic training process in which stunt actors replicate movement patterns commonly observed among older adults.[34] Conditions such as kyphosis and osteoporosis can alter posture and movement, while sarcopenia can reduce muscle mass and neuropathy can affect gait and foot placement.[35,36] Trained stunt actors were used to perform a range of fall scenarios representative of activities of daily living. Because asking older adults to simulate falls raises ethical and safety concerns, trained stunt actors provide a feasible alternative that supports scenario diversity while minimizing participant risk.[20,34,37]

In addition to dataset limitations, evaluation approaches for fall detection systems remain highly heterogeneous. Previous studies have employed a wide range of sensor modalities, including wearable, vision-based, ambient, and hybrid systems, together with analytical approaches such as threshold-based methods, machine learning, and deep learning techniques.[17,18] Variations in datasets, experimental conditions, and performance metrics make comparisons across studies difficult and limit the generalizability of findings.[21] The absence of standardized validation frameworks further reduces reproducibility and hinders implementation in real-world care environments. Although advances in AI and IoT technologies have enabled continuous monitoring, challenges related to environmental variability, workflow integration, and user interaction remain insufficiently addressed in long-term settings.[17]

The purpose of this protocol paper is to present a pragmatic and replicable methodology for validating contactless fall detection systems in long-term care environments. By combining structured stunt-actor testing with continuous real-world monitoring, the protocol is intended to support ecologically valid evaluation while providing a framework for future validation studies of contactless monitoring technologies.

Methods

This project was structured into three distinct phases and involved the development of a research protocol to validate a contactless fall detection system. This study presents a validation protocol rather than an interventional clinical trial protocol; therefore, clinical trial reporting guidelines, such as the Standard Protocol Items: Recommendations for Interventional Trials (SPIRIT), were not considered applicable. The research was conducted at two sites located in Columbia, Missouri, and Tucson, Arizona, USA. The validation process used prototype hardware, with technical support provided by Signify N.V. (formerly Philips Lighting; Eindhoven, the Netherlands). Its role was limited to providing equipment and technical assistance; Signify N.V. did not participate in study design, data analysis, interpretation of findings, or manuscript preparation.

Although Standards for Reporting Diagnostic Accuracy Studies 2015 (STARD) was developed primarily for reporting completed diagnostic accuracy studies, relevant STARD elements were considered during protocol development. These included detailed descriptions of participant eligibility, index test procedures, reference standards, event verification methods, handling of indeterminate events, and planned accuracy analyses to enhance transparency and reproducibility.

Figure 1 provides an overview of the three phases. Phase 1 (Pre-Implementation Assessment) involved evaluating real-world test sites to ensure infrastructure readiness for system deployment. Phase 2 (System Implementation and Training) included sensor installation, system calibration, and personnel training. Phase 3 (System Verification) involved validation testing in long-term care facilities under real-world conditions.

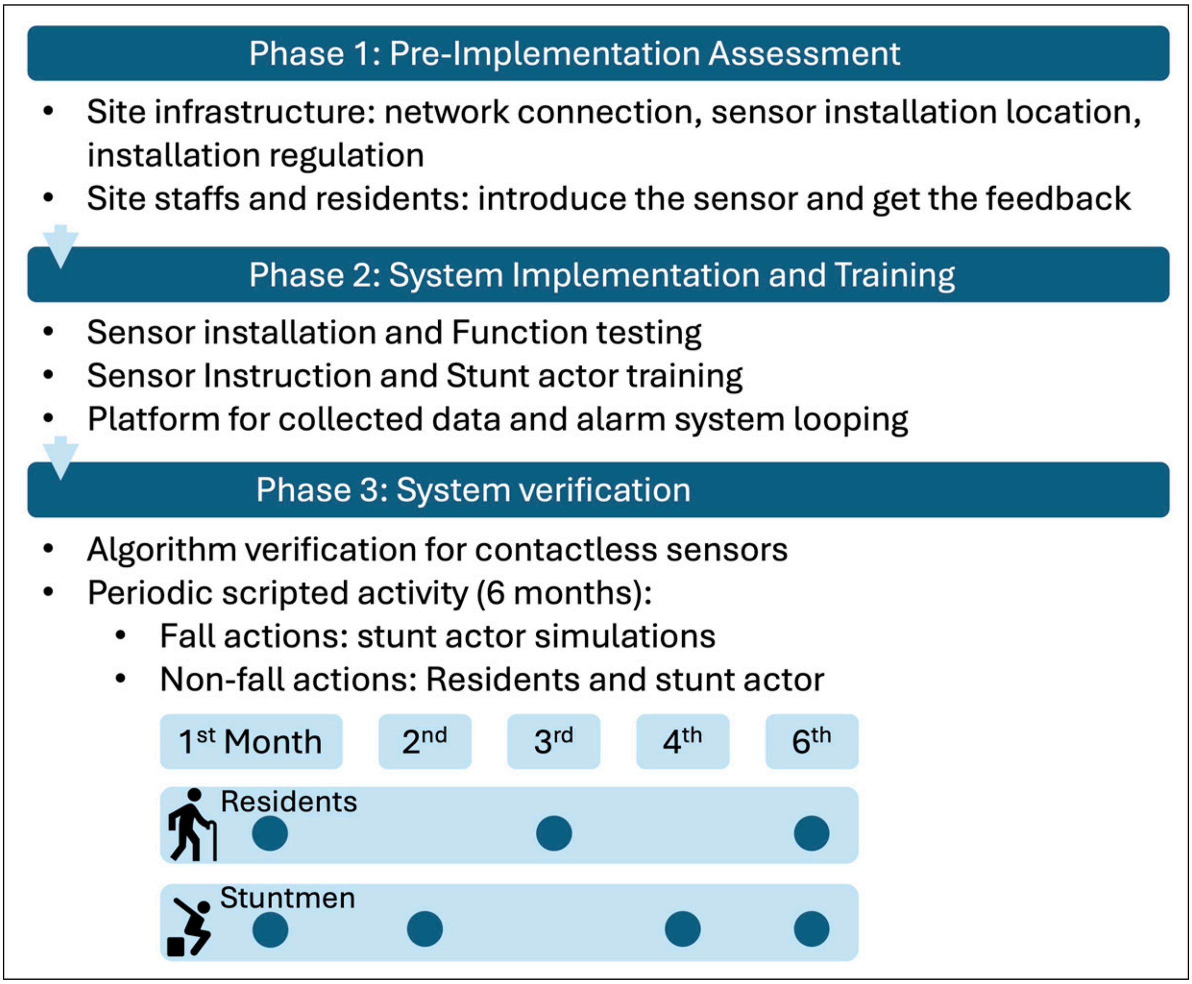

Figure 1. Phases and tasks of the protocol.

Phase 1: Pre-implementation assessment

In Phase 1, the infrastructure at each test site was evaluated to determine its suitability for system verification. A layered architecture has previously been described as a generic framework for sensing and monitoring systems.[38] This framework consists of four layers: the Physiological Sensing Layer (PSL), Local Communication Layer (LCL), Information Processing Layer (IPL), and User Application Layer (UAL).[38] This conceptual framework guided the assessment of the system architecture shown in Figure 2.

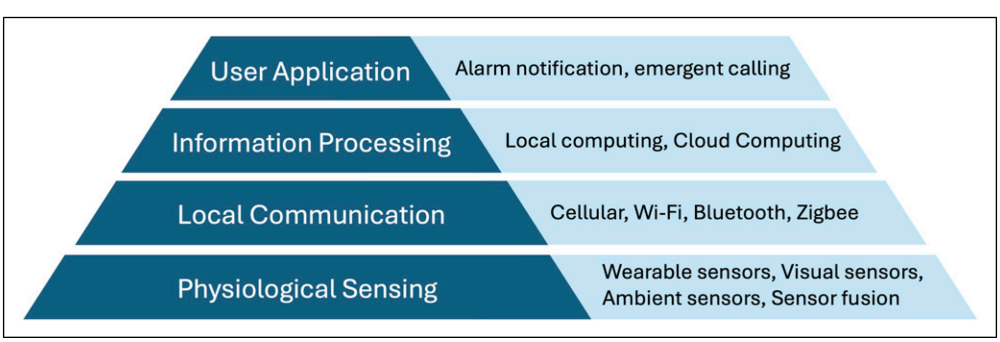

Figure 2. The main components of the fall detection system consisted of four layers.

Within the PSL, sensors, including accelerometers, ambient devices, and visual sensors, are used to collect physiological and environmental data. The LCL supports transmission of these data through technologies such as Wi-Fi, Bluetooth, or Zigbee. The IPL is responsible for data processing and analysis using local or cloud-based computing resources. Finally, the UAL includes applications that deliver information to end users, such as fall alerts and caregiver notifications. Figure 2 illustrates these four generic layers and provides examples of their implementation in the fall detection system under evaluation.

During this phase, site assessments focused on determining whether the required infrastructure was available across all four layers. For example, the LCL required stable network connectivity; therefore, facilities without suitable Wi-Fi or Bluetooth support were identified as needing upgrades or alternative solutions, such as portable routers, before deployment. This preparatory step ensured that essential conditions, including sensor placement feasibility, network capacity, and integration requirements, were established before proceeding to Phase 2.

In conjunction with evaluating technology infrastructure, Phase 1 also involved a review of each site to ensure compliance with local safety and electrical regulations. The contactless fall detection system used in this study was embedded within lighting fixtures and required professional installation. This approach ensured that the equipment was installed according to facility standards, thereby minimizing safety risks and supporting stable system operation during subsequent phases.

Understanding caregivers' and residents' perspectives regarding system implementation was also an important component of Phase 1. Early engagement with caregivers provided insights into existing workflows and daily operations, which informed strategies for integrating the detection system into routine care practices. Residents, as primary users of the system, also provided feedback regarding sensor placement and interactions with the technology.[39]

To support adoption, the protocol emphasized early communication, orientation, and training for both staff and residents. Feedback was actively solicited throughout implementation and addressed collaboratively, allowing adjustments to be made in response to identified usability and operational concerns. This user-centered approach was intended to address the needs of both staff and residents while supporting acceptance of fall detection systems in long-term care environments.

Phase 2: System implementation and training

In Phase 2, the fall detection system was implemented at the designated test facilities. Building on the assessments conducted during Phase 1, this phase focused on deploying the hardware and software, calibrating sensors to accommodate local environmental conditions, and orienting staff to system operation. Installation was coordinated with facility staff to minimize disruption to daily activities, and a calibration period was included to account for factors such as room layout, lighting, and sensor positioning. For example, depth sensors, which may be affected by infrared interference, were tested in situ to ensure proper operation.

The staff orientation included instruction on basic system operation, troubleshooting procedures, and user interactions with contact-based devices, where applicable (e.g., wristbands). Simplified procedures were provided when necessary to accommodate residents with cognitive impairments and reduce reliance on caregiver assistance. Designated technical personnel were identified and trained to provide on-site support for system-related needs throughout the study.

As a preparatory component of Phase 3, the protocol specified that stunt actors be healthy adults who were physically capable of performing scripted fall and non-fall activities without increased risk of injury. Prior stunt, healthcare, or caregiving experience was not required. Each eligible stunt actor completed a single structured training session of approximately two hours during Phase 2. Training involved video review of actual fall incidents, use of an aging simulation suit (Figure 3(a)), and practice of all scripted fall and non-fall scenarios listed in Table 1 (Figure 3(b)).[34] Scripted fall activities were categorized into four groups: (1) falls from a standing position, (2) falls involving trips or slips, (3) falls from a seated position, and (4) falls from a bed or couch. Training also addressed postural and movement adaptations commonly associated with conditions such as kyphosis and sarcopenia to support realistic performance. No predetermined number of repetitions was required. Instead, practice continued as needed until a nursing expert determined that the actor demonstrated adequate understanding of the procedures, safety awareness, and readiness to perform the scripted activities during Phase 3. The training established the general sequence, safety requirements, and movement characteristics of each scenario while allowing variation across actors, thereby preserving natural variation in movement patterns. Additional instruction or practice was provided when actors required further preparation or were unable to perform an activity safely. Actors could discontinue participation at any time if they were unwilling or unable to complete the activities safely.

Phase 3: System verification

In Phase 3, verification testing of the fall detection system commenced following installation and calibration. This phase represented the most extensive component of the protocol and consisted of a six-month real-world study conducted at two

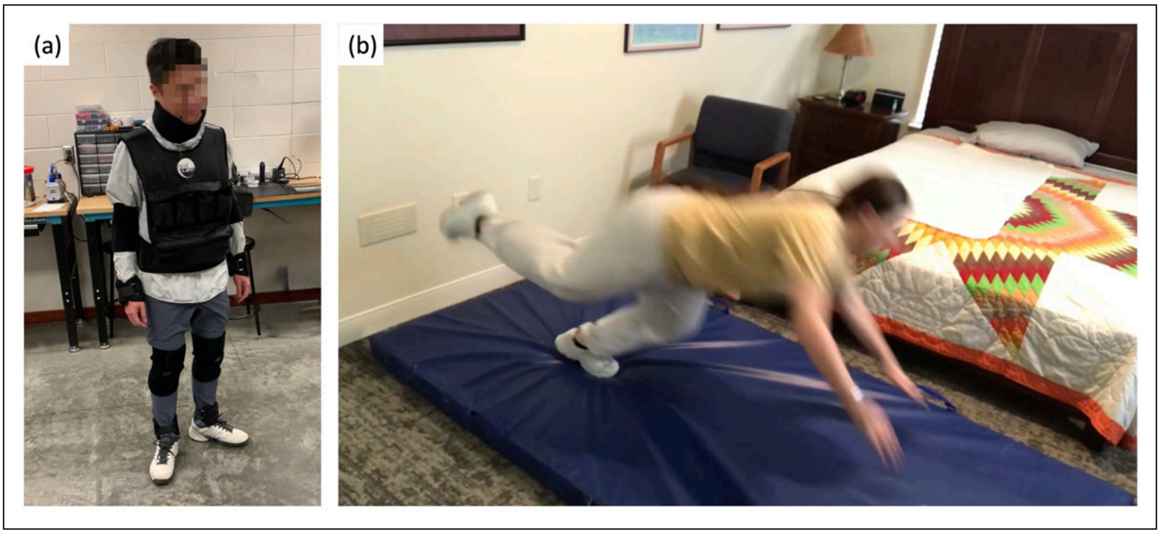

Figure 3. (a) The participant is wearing an aging simulation suit, which includes joint restrictors and weighted bands. (b) The participant enacts a scripted fall scenario simulating an older adult falling in a resident's room.

sites: a senior independent living community and a senior assisted living and memory care facility. The primary objective was to establish a structured protocol for evaluating system accuracy, reliability, and feasibility in real-world long-term care environments.

Instrumentation

The fall detection system incorporated two sensor modalities. First, radar sensors were integrated into ceiling-mounted light fixtures in residents' bedrooms to provide continuous monitoring of posture and movement. Second, time-of-flight (ToF) non-visible depth sensors were embedded within bathroom light fixtures to capture fall-related events in high-risk locations. Placement of the ToF sensors at ceiling height provided broad spatial coverage of the functional area within each room.

To support event verification, low-resolution cameras were co-located with the radar sensors within the same device housing. This configuration ensured spatial alignment between sensing modalities. The cameras generated approximate body silhouettes that were used exclusively to verify fall alerts while protecting residents' privacy. Radar sensors combined with low-resolution cameras were deployed in bedrooms to support continuous monitoring, whereas ToF sensors were used in bathrooms because these areas required greater privacy protection. All sensors were integrated into existing lighting infrastructure and supplied by Signify for use in this study. While specific sensor modalities were evaluated in this protocol, the proposed validation framework may also be applied to other sensing technologies that support continuous monitoring, adequate spatial coverage, and privacy-preserving operation.

Sampling and procedures

To supplement data obtained through continuous monitoring, trained stunt actors performed scripted scenarios in residents' rooms once every two months. These scenarios were based on the training program described in Phase 2 and included both fall and non-fall activities representative of older adults' daily routines. The activities were divided into two sets, each containing both fall and non-fall scenarios, and actors were randomly assigned to one set during each testing session to reduce predictability. The testing schedule was determined based on feasibility and the need to capture variability in real-world conditions. Older residents were not asked to simulate falls. They could voluntarily perform scripted non-fall actions, such as standing up from a chair or bending to retrieve an object, to support the assessment of system specificity under real-world conditions.

Event verification

For scripted testing sessions, the activity performed, its classification (fall or non-fall), and its start and end times were documented in a scripted activity log immediately following each action. These contemporaneous records served as the

Table 1. Scripted actions for stunt actor training.

Scripted non-fall actions
- Walk slowly for about 10 seconds - Walk at a moderate speed for about 10 seconds - Step up and down from a low stool with a hard landing (for stunt actors only) - Bend over to tie shoes - Pick something up from the floor - Sit down and stand up from a toilet seat - Flop down hard into an armchair (or any chair) and then stand up - Sit down on a bed and stand up - Flop down hard, then lie down, and then stand up from a bed - Throw linens onto the floor - Remove clothing (e.g., a jacket) and throw it on the floor - If available, have a pet jump off a chair or bed
Scripted falls actions
1. Falls from a standing position Due to loss of balance, the subject leans forward, to the left, to the right, or backward; looks down; and when falling, tries to break the fall with upper extremities. - Fall forward - Fall to the left side - Fall to the right side - Fall backward Due to transient loss of consciousness, falls like a tree, toppling backward, forward, or to the side; crumples to the floor; and makes no attempt to break the fall with upper extremities - Fall forward - Fall to the right side - Fall to the left side - Fall straight down - Fall backward **2. Falls involving trips and slips** While walking, the subject trips or slips: walks with a shortened stride; leans forward; looks down; and when falling, tries to break the fall with upper extremities. - Trip and fall forward - Trip and fall to the side - Slip and fall forward - Slip and fall to the side **3. Falls from a sitting position** From an initial position sitting on a chair: leans, causing a change in center of gravity, and falls off the chair; attempts to break the fall with upper extremities. - Fall forward from a stationary chair - Fall to the right side from a stationary chair - Fall to the left side from a stationary chair - Fall by sliding forward out of a chair (with wheels) as it slides back - Fall by sliding backward out of a chair (with wheels) as it slides back **4. Falls from bed or couch** Somewhat awakens and attempts to get up: starts sleeping (lying position); attempts to get up, legs get caught in a blanket, and falls; attempts to break the fall with upper extremity - Fall to the side, with the upper body falling first Does not awaken: rolls too close to the edge of the bed or couch, causing a change in center of gravity, and rolls off; makes no attempt to break the fall with the upper extremity - Fall to the side, with hips and shoulders falling first

reference standard for matching scripted activities with events detected by the system. System alerts generated during testing sessions were received and reviewed in real time by the research team.

For naturally occurring events, alerts were transmitted to both facility caregivers and the research team. Caregivers conducted on-site verification and documented confirmed falls according to routine facility incident-reporting procedures. The corresponding incident report served as the primary documentary source for the research team. When no fall was identified, caregivers communicated this determination to the research team, and the event was documented in the study event log.

Facility caregivers also reported resident falls identified during routine care, including falls for which no system alert had been generated. Confirmed falls were cross-referenced with the system alert log to determine whether a corresponding alert had been generated. Caregiver assessment served as the primary reference standard for classifying naturally occurring events.

Low-resolution video was used only as an auxiliary source when timely on-site verification was not possible or when additional information was needed. In such cases, video data were reviewed in conjunction with caregiver assessment to support classification of the event. Events that could not be classified after review of all available information were designated as indeterminate and summarized separately.

Event classification and planned analysis

During scripted testing, each fall or non-fall activity constituted an event-level evaluation opportunity. System outcomes were classified into four predefined categories: (1) True Positive (TP): a fall occurred and an alert was generated; (2) True Negative (TN): no fall occurred and no alert was generated; (3) False Positive (FP): an alert was generated when no fall occurred; and (4) False Negative (FN): a fall occurred without generating an alert. Sensitivity was calculated as TP/(TP + FN), and specificity was calculated as TN/(TN + FP). Event frequencies and distributions were summarized descriptively across scripted scenarios.

For continuous real-world monitoring, caregiver-confirmed falls were cross-referenced with the system alert log. A confirmed fall with a corresponding system alert was classified as a true positive, whereas a confirmed fall without a corresponding alert was classified as a false negative. Alerts for which caregiver verification determined that no fall had occurred were classified as false positives. The burden of false-positive alerts was standardized according to observation time and summarized as the number of false-positive alerts per 1,000 monitored resident-days. Monitored resident-days were calculated by summing the valid monitoring days contributed by all participating residents, including those residing in both single- and multiple-occupancy rooms.

Indeterminate events were excluded from TP, TN, FP, and FN classifications and from sensitivity and specificity calculations. These events were documented and summarized separately using descriptive statistics. Periods of system downtime, unavailable data, or documented environmental conditions that disrupted normal sensor operation were excluded from valid observation time and summarized separately. No formal sample-size calculation was performed because the purpose of the protocol was to capture repeated fall and non-fall observations under real-world conditions rather than to test a predefined statistical hypothesis.

The protocol distinguished between operational confounders occurring during otherwise valid monitoring and temporary conditions that rendered the monitoring period invalid. Alerts associated with identifiable non-fall activities during valid monitoring, such as pet movement, were classified as false-positive alerts and included in summaries of false-alert burden. In contrast, periods affected by conditions that substantially altered sensor operation or coverage, such as renovation, maintenance, calibration, or sensor relocation, were excluded from valid observation time. The reason and duration of each invalid monitoring period were documented and summarized separately. The repeated execution of scripted activities at predefined intervals was intended to provide standardized reference data while reducing the ethical concerns associated with asking older adults to simulate falls.

Troubleshooting and refinements

During preliminary testing, several challenges were identified and addressed to refine the verification protocol. First, observations revealed that the remote sensing technology deployed in bedrooms required a longer reset period to distinguish successive fall events. The protocol was therefore revised to incorporate a 20-second dwell time on the floor following a fall, followed by a one-minute reset interval during which stunt actors exited the sensing field. The use of protective mats to reduce injury risk during scripted falls also created challenges for the ToF sensor in bathroom settings. The increased floor height caused by the mats positioned stunt actors outside the sensor's optimal detection range. Following consultation with industry engineering partners, the protocol was modified to include a 2-minute adaptation period that allowed the ToF sensor to adjust to the altered environmental conditions before testing resumed. These adjustments were intended to improve the system's ability to distinguish successive scripted fall events.

Second, preliminary testing highlighted the need to distinguish between environmental activities that generated false alerts during otherwise valid monitoring and temporary conditions that disrupted normal sensor operation. Pet movement was identified as a potential source of operational false alerts, whereas apartment renovation or maintenance activities could create periods during which sensor observations were not considered valid. These observations informed refinement of the protocol's documentation and analysis procedures.

Finally, preliminary testing supported the use of low-resolution video as an auxiliary source when caregiver verification was delayed or additional information was needed. Video data were not used as a primary reference source but were reviewed in conjunction with caregiver assessment to assist with event classification when necessary. This refinement was incorporated into the event verification process while maintaining the protocol's privacy-preserving approach.

Strengths and limitations

Strengths

This paper presents a study protocol describing practical procedures for validating contactless fall detection systems in long-term care environments. The protocol outlines site assessment, system implementation, stunt-actor training, scripted testing, continuous monitoring, event verification, and planned analysis procedures. By focusing on validation methodology rather than performance outcomes, it provides a framework that may support reproducible evaluation across settings.

The use of contactless sensors embedded within existing infrastructure enables continuous monitoring while reducing challenges commonly associated with wearable devices, including loss, discomfort, charging requirements, and inconsistent use.[40,41] These considerations may be particularly relevant for older adults with cognitive impairment, who often experience difficulties managing wearable technologies.[42,43]

Another strength is the use of trained stunt actors to perform scripted fall and non-fall activities. This approach allows the collection of reference events while avoiding the ethical concerns associated with asking older adults to simulate falls. The use of trained stunt actors supports collection of reference events without requiring older adults to simulate falls.

The protocol also distinguishes between verification procedures for scripted and naturally occurring events. Scripted activities are verified using activity logs and timestamps, whereas caregiver confirmation serves as the primary reference for naturally occurring events, with low-resolution video used as supplementary information when needed. Together, these procedures support a structured approach to event verification in long-term care environments.

Limitations

This protocol has several limitations that should be considered in future applications. First, although the use of trained stunt actors provides a safer alternative to asking older adults to simulate falls, simulated events may not fully capture the unpredictability, physiological responses, and contextual factors associated with naturally occurring falls among frail older adults. Although the training procedures were intended to reproduce selected age-related postural and movement characteristics, they may not fully represent the effects of frailty, cognitive impairment, neuromuscular deficits, or other clinical conditions.

Second, naturally occurring falls may be relatively infrequent during the monitoring period and may not represent the full range of possible fall scenarios. Combining scripted and naturally occurring events may also introduce variability in event characteristics, which should be considered when interpreting results or applying the protocol in different settings.

Third, caregiver confirmation serves as the primary reference for naturally occurring events. Falls that are not directly observed, documented, or subsequently identified by caregivers may not be captured. In addition, low-resolution video may not always provide sufficient information to resolve uncertain events. Events that remain unclassifiable should therefore be documented and summarized separately as indeterminate.

Fourth, installation of the sensor-integrated lighting fixtures required removal of ceiling fans previously used by some residents. This environmental modification may have affected air circulation and thermal comfort within residents' rooms and could potentially have influenced daily activities. Stationary fans were provided to address this concern.

Finally, preliminary testing identified operational considerations that may affect future implementations, including the need for adequate reset intervals and the effects of environmental activities such as pet movement, maintenance, and renovation. These factors should be documented and considered when defining valid observation time and interpreting false-alert burden.

Conclusion

This protocol describes a pragmatic multidisciplinary framework for validating contactless fall detection systems in long-term care environments. The framework incorporates infrastructure assessment, system implementation, stunt-actor training, scripted testing, continuous monitoring, event verification, and predefined analytical procedures.

The protocol was designed to support field-based evaluation while accounting for safety, privacy, environmental variability, and existing care workflows. By combining structured reference testing with real-world monitoring, it provides an approach for generating validation data under operational conditions. Because this article focuses on protocol development rather than system performance outcomes, future studies are needed to apply the protocol across different sensor platforms, care settings, and resident populations to evaluate its reproducibility, generalizability, and operational feasibility across diverse care settings.

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Ethical considerations

The experimental protocols were approved by the Institutional Review Board (IRB) of the University of Missouri (No. 2095619) on August 27, 2023. All research activities complied with ethical regulations and were performed in accordance with regulations of each hospital.

Author contributions

All authors are responsible for the reported research. CCC, AHJ, MS, and SFW conceived and designed the study protocol. CCC and AHJ developed the data collection procedures. CCC, AHJ, MS, and SFW contributed to the design of the analysis and data interpretation plan. CCC, AHJ, and SFW wrote the first draft of the manuscript. All authors (CCC, AHJ, MS, and SFW) reviewed and edited the manuscript and approved the final version for submission.

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Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Guarantor

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References

1. Cameron EJ, Bowles SK, Marshall EG, et al. Falls and long-term care: a report from the care by design observational cohort study. *BMC Fam Pract* 2018; 19: 73, 20180524. https://doi.org/10.1186/s12875-018-0741-6
2. Thapa R, Garikipati A, Shokouhi S, et al. Predicting Falls in Long-term Care Facilities: Machine Learning Study. *JMIR Aging* 2022; 5: e35373, 20220401. https://doi.org/10.2196/35373
3. Moreland B, Kakara R and Henry A. Trends in Nonfatal Falls and Fall-Related Injuries Among Adults Aged ≥ 65 Years — United States, 2012-2018. *MMWR Morb Mortal Wkly Rep* 2020; 69: 875–881, 20200710. https://doi.org/10.15585/mmwr.mm6927a5
4. Florence CS, Bergen G, Atherly A, et al. Medical Costs of Fatal and Nonfatal Falls in Older Adults. *J Am Geriatr Soc* 2018; 66: 693–698, 20180307. https://doi.org/10.1111/jgs.15304
5. National Center for Injury Prevention and Control. *Cost of older adult falls*, 2020. https://stacks.cdc.gov/view/cdc/122747 (accessed 23 July 2025).
6. Cipriani G, Danti S, Picchi L, et al. Daily functioning and dementia. *Dement Neuropsychol* 2020; 14: 93–102. https://doi.org/10.1590/1980-57642020dn14-020001

7. Centers for Disease Control Prevention. Facts about falls. Older adult fall prevention. https://www.cdc.gov/falls/data-research/facts-stats/index.html (2026, accessed 19 Feburary 2026).
8. Liu JY. Fear of falling in robust community-dwelling older people: results of a cross-sectional study. *J Clin Nurs* 2015; 24: 393–405, 20140502. https://doi.org/10.1111/jocn.12613
9. Chaudhuri S, Kneale L, Le T, et al. Older Adults' Perceptions of Fall Detection Devices. *J Appl Gerontol* 2017; 36: 915–930, 20150624. https://doi.org/10.1177/0733464815591211
10. Garcia Reyes EP, Kelly R, Buchanan G, et al. Understanding Older Adults' Experiences With Technologies for Health Self-management: Interview Study. *JMIR Aging* 2023; 6: e43197, 20230321. https://doi.org/10.2196/43197
11. Taylor E, Goodwin VA, Ball S, et al. Older Adults' Perspectives of Independence Through Time: Results of a Longitudinal Interview Study. *Gerontologist* 2024; 64: gnad073. https://doi.org/10.1093/geront/gnad073
12. Cullen A, Mazhar MKA, Smith MD, et al. Wearable and Portable GPS Solutions for Monitoring Mobility in Dementia: A Systematic Review. *Sensors (Basel)* 2022; 22: 3336, 20220427. https://doi.org/10.3390/s22093336
13. Facchinetti G, Petrucci G, Albanesi B, et al. Can Smart Home Technologies Help Older Adults Manage Their Chronic Condition? A Systematic Literature Review. *Int J Environ Res Public Health* 2023; 20: 1205, 20230110. https://doi.org/10.3390/ijerph20021205
14. Lee-Cheong S, Amanullah S and Jardine M. New assistive technologies in dementia and mild cognitive impairment care: A PubMed review. *Asian J Psychiatr* 2022; 73: 103135, 20220422. https://doi.org/10.1016/j.ajp.2022.103135
15. Flor-Unda O, Arcos-Reina R, Estrella-Caicedo C, et al. A Comparative Overview of Technological Advances in Fall Detection Systems for Elderly People. *Sensors (Basel)* 2025; 25: 7423, 20251205. https://doi.org/10.3390/s25247423
16. Gharghan SK and Hashim HA. A comprehensive review of elderly fall detection using wireless communication and artificial intelligence techniques. *Measurement* 2024; 226: 114186. https://doi.org/10.1016/j.measurement.2024.114186
17. Mohan D, Al-Hamid DZ, Chong PHJ, et al. Artificial intelligence and IoT in elderly fall prevention: a review. *IEEE Sensors Journal* 2024; 24: 4181–4198. https://doi.org/10.1109/jsen.2023.3344605
18. Nahian MJA, Raisa JF, Mahmud M, et al. Artificial Intelligence for Elderly Fall Detection: State-of-the-art Methods, Applications and Challenges. *Cognitive Computation* 2026; 18: 12. https://doi.org/10.1007/s12559-026-10550-5
19. Wrede C, Braakman-Jansen A and van Gemert-Pijnen L. Requirements for Unobtrusive Monitoring to Support Home-Based Dementia Care: Qualitative Study Among Formal and Informal Caregivers. *JMIR Aging* 2021; 4: e26875, 20210412. https://doi.org/10.2196/26875
20. Wang X, Ellul J and Azzopardi G. Elderly fall detection systems: A literature survey. *Frontiers in Robotics and AI* 2020; 7: 71. https://doi.org/10.3389/frobt.2020.00071
21. Gorce P and Jacquier-Bret J. Fall Detection in Elderly People: A Systematic Review of Ambient Assisted Living and Smart Home-Related Technology Performance. *Sensors* 2025; 25: 6540. https://doi.org/10.3390/s25216540
22. Ghorayeb A, Comber R and Gooberman-Hill R. Older adults' perspectives of smart home technology: Are we developing the technology that older people want? *International Journal of Human-Computer Studies* 2021; 147: 102571. https://doi.org/10.1016/j.ijhcs.2020.102571
23. Galambos C, Rantz M, Back J, et al. Older Adults' Perceptions of and Preferences for a Fall Risk Assessment System: Exploring Stages of Acceptance Model. *Comput Inform Nurs* 2017; 35: 331–337. https://doi.org/10.1097/CIN.0000000000000330
24. Demiris G, Oliver DP, Giger J, et al. Older adults' privacy considerations for vision based recognition methods of eldercare applications. *Technol Health Care* 2009; 17: 41–48. https://doi.org/10.3233/THC-2009-0530
25. Wild K, Boise L, Lundell J, et al. Unobtrusive In-Home Monitoring of Cognitive and Physical Health: Reactions and Perceptions of Older Adults. *J Appl Gerontol* 2008; 27: 181–200. https://doi.org/10.1177/0733464807311435
26. Farber N, Shinkle D, Lynott J, et al. *Aging in place: a state survey of livability policies and practices*. AARP Public Policy Institute, 2011.
27. Zhang Z, Genc Y, Wang D, et al. Effect of AI Explanations on Human Perceptions of Patient-Facing AI-Powered Healthcare Systems. *J Med Syst* 2021; 45: 64, 20210504. https://doi.org/10.1007/s10916-021-01743-6
28. Lee A, Lee H and Lee S-H. Digital Healthcare Approaches for Fall Detection and Prediction in Older Adults: A Systematic Review of Evidence from Hospital and Long-Term Care Settings. *Medicina* 2025; 61: 1926. https://doi.org/10.3390/medicina61111926
29. Vollmer Dahlke D, Lee S, Smith ML, et al. Attitudes Toward Technology and Use of Fall Alert Wearables in Caregiving: Survey Study. *JMIR Aging* 2021; 4: e23381, 20210127. https://doi.org/10.2196/23381
30. Ben-Sadoun G, Michel E, Annweiler C, et al. Human Fall Detection Using Passive Infrared Sensors with Low Resolution: A Systematic Review. *Clin Interv Aging* 2022; 17: 35–53, 20220113. https://doi.org/10.2147/CIA.S329668
31. Casilari E, Santoyo-Ramón JA and Cano-García JM. UMAFall: A Multisensor Dataset for the Research on Automatic Fall Detection. *Procedia Computer Science* 2017; 110: 32–39. https://doi.org/10.1016/j.procs.2017.06.110
32. Espinosa R, Ponce H, Gutierrez S, et al. A vision-based approach for fall detection using multiple cameras and convolutional neural networks: A case study using the UP-Fall detection dataset. *Comput Biol Med* 2019; 115: 103520, 20191030. https://doi.org/10.1016/j.compbiomed.2019.103520

33. Newaz NT and Hanada E. The Methods of Fall Detection: A Literature Review. *Sensors (Basel)* 2023; 23: 5212, 20230530. https://doi.org/10.3390/s23115212
34. Rantz MJ, Aud MA, Alexander G, et al. Falls, technology, and stunt actors: new approaches to fall detection and fall risk assessment. *J Nurs Care Qual* 2008; 23: 195–201. https://doi.org/10.1097/01.NCQ.0000324581.59557.42
35. Clegg A, Young J, Iliffe S, et al. Frailty in elderly people. *Lancet* 2013; 381: 752–762, 20130208. https://doi.org/10.1016/S0140-6736(12)62167-9
36. Doody P, Lord JM, Greig CA, et al. Frailty: Pathophysiology, Theoretical and Operational Definition(s), Impact, Prevalence, Management and Prevention, in an Increasingly Economically Developed and Ageing World. *Gerontology* 2023; 69: 927–945, 20221207. https://doi.org/10.1159/000528561
37. Stone EE and Skubic M. Fall detection in homes of older adults using the Microsoft Kinect. *IEEE J Biomed Health Inform* 2015; 19: 290–301, 20140317. https://doi.org/10.1109/JBHI.2014.2312180
38. Ray PP. Home health hub Internet of Things (H3IoT): an architectural framework for monitoring health of elderly people. In: *T3 - Proc Int Conf Sci Eng Manag Res (ICSEMR)*. IEEE, 2014, pp. 1–6.
39. Johnson AH, Chen CC, Fauss KM, et al. The lived experience of older adults with monitoring technologies: an interpretive phenomenology study. *Healthcare* 2026; 14: 288, 20260123. https://doi.org/10.3390/healthcare14030288
40. Chung J, Brakey HR, Reeder B, et al. Community-dwelling older adults' acceptance of smartwatches for health and location tracking. *Int J Older People Nurs* 2023; 18: e12490, 20220712. https://doi.org/10.1111/opn.12490
41. Reeder B, Chung J, Lyden K, et al. Older women’s perceptions of wearable and smart home activity sensors. *Inform Health Soc Care* 2020; 45: 96–109, 20190328. https://doi.org/10.1080/17538157.2019.1582054
42. Rocha IC, Arantes M, Moreira A, et al. Monitoring Wearable Devices for Elderly People with Dementia: A Review. *Designs* 2024; 8: 75. https://doi.org/10.3390/designs8040075
43. Shin HR, Um SR, Yoon HJ, et al. Comprehensive Senior Technology Acceptance Model of Daily Living Assistive Technology for Older Adults With Frailty: Cross-sectional Study. *J Med Internet Res* 2023; 25: e41935, 20230410. https://doi.org/10.2196/41935