In-Home Positioning for Remote Home Health Monitoring in Older Adults: A Systematic Review

Andrew Chan, Joanne Cai, Linna Qian, Brendan Coutts, Steven Phan, Geoff Gregson, Michael Lipsett, Adriana Ríos Rincón

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Abstract

Background: With the growing proportion of Canadians over 65 years old, smart home and health monitoring technologies may help older adults to manage chronic disease and support aging-in-place. Localization technologies have been used to support management of frailty and dementia by detecting activities in the home.

Objective: This systematic review aims to summarize the clinical evidence for in-home localization technologies, review the acceptability of monitoring, and summarize the range of technologies being used for in-home localization.

Methods: PRISMA methodology was followed and the protocol was registered with PROSPERO. MEDLINE, EMBASE, CINAHL and Scopus were searched with two reviewers performing screening, extractions and quality assessments.

Results: A total of 1935 articles were found, with 36 technology-focused articles and 10 that reported on patient outcomes. From moderate to high quality studies, two studies reported mixed results on identifying mild cognitive dementia or frailty, while four studies reported mixed results on acceptability of localization technology. Technologies included ambient sensors, Bluetooth or Wifi received signal strength to localizer tags using RFID, UWB, Zigbee or GPS, and inertial measurement units with localizer tags.

Conclusions: Clinical utility of localization remains mixed, with in-home sensors not being able to identify between older adults with healthy cognition from older adults with mild cognitive impairment. However, frailty was detectable using in-home sensors. Acceptability is moderately positive, particularly with ambient sensors. Localization technologies can achieve room detection accuracies up to 92% and linear accuracies of up to 5-20cm that may be promising for future clinical applications. Clinical Trial: PROSPERO (ID:CRD 42022339845)

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Abstract

Introduction: With the growing proportion of Canadians over 65 years old, smart home and health monitoring technologies may help older adults to manage chronic disease and support aging-in-place. Localization technologies have been used to support management of frailty and dementia by detecting activities in the home. **Methods:** This systematic review aims to summarize the clinical evidence for in-home localization technologies, review the acceptability of monitoring, and summarize the range of technologies being used for in-home localization. PRISMA methodology was followed and the protocol was registered with PROSPERO. MEDLINE, EMBASE, CINAHL and Scopus were searched with two reviewers performing screening, extractions and quality assessments. **Results:** A total of 1935 articles were found, with 36 technology-focused articles and 10 that reported on patient outcomes. From moderate to high quality studies, two studies reported mixed results on identifying mild cognitive dementia or frailty, while four studies reported mixed results on acceptability of localization technology. Technologies included ambient sensors, Bluetooth or Wifi received signal strength to localizer tags using RFID, UWB, Zigbee or GPS, and inertial measurement units with localizer tags. **Discussion:** Clinical utility of localization remains mixed, with in-home sensors not being able to identify between older adults with healthy cognition from older adults with mild cognitive impairment. However, frailty was detectable using in-home sensors. Acceptability is moderately positive, particularly with ambient sensors. Localization technologies can achieve room detection accuracies up to 92% and linear accuracies of up to 5-20cm that may be promising for future clinical applications.

Introduction

The proportion of Canadians over 65 is growing from 7 million in 2020 to an estimated 9.5 million by 2030 (23% of the population) by 2030, (Canada, 2016; Ferrucci et al., 2008; Government of Canada, 2020). With the ratio of adults aged 15-64 to persons aged 65 and older halving from 7.2 in 1980 to 3.6 in 2020, the question of how to maintain a sustainable health care system in the face of these changing demographics remains a top priority (Canada, 2016). Transforming care processes by using digital platforms and remote monitoring tools may be able to address our increasingly aged population and higher life expectancies (Islind et al., 2019). Smart home and health monitoring technologies have been touted as the future of managing chronic diseases and allowing people to age in place (Alam et al., 2012; Liu et al., 2016; Narasimhan et al., 2021; Piau et al., 2019).

Aging is often accompanied by a gradual decrease in physical and mental capacity (Holliday, 1995; Xue, 2011). In-home monitoring technologies have been used to support older adults to age in place by detecting and managing worsening physical and cognitive decline (Brims & Oliver, 2019; Cote et al., 2021; Dasenbrock et al., 2016; Gallucci et al., 2020; Godfrey et al., 2019; Khan et al., 2018; Mugueta-Aguinaga & Garcia-Zapirain, 2017; Narasimhan et al., 2021; Piau et al., 2019; Teh et al., 2022; Vavasour et al., 2021). Wearables including accelerometers and gyroscopes have been used to monitor postural transitions (Parvaneh et al., 2017) and provide yearly gait speed assessments (White et al., 2013), while weight scales and grip balls have been used to monitor changes in weight and grip strength (Chkeir et al., 2019). Actigraphy has been commonly used in cross-sectional studies on

physical activity and gait alongside ambient sensors (Dasenbrock et al., 2016) and to monitor behavioral changes such as agitation and aggression (Cote et al., 2021; Khan et al., 2018).
While actigraphy can give some quantitative idea of the amount of movement happening it lacks contextual data that could allow for targeted interventions and improved interpretation of activity data (Godfrey et al., 2019; Hunter & Divine, 2018; Kikkert et al., 2018; Persad et al., 2008). Ambient monitors, including infrared sensors and magnetic door contact sensors, can detect which room a resident is in to provide some context of the activities performed (Kaye et al., 2018; Lach et al., 2019; Rahal et al., 2008). Wearable tags using wireless technologies like Bluetooth or Wifi, can also be used to localize residents in their homes, offering 1.5-5m accuracy (Hung et al., 2021; Montoliu et al., 2020).
The primary objective of this study is to systematically review the clinical evidence for indoor localization technologies to support in-home monitoring of older adults. Secondary objectives include:

- To review the acceptability of in-home positioning technologies and,
- To summarize the range of localization technologies being developed

Methodology

Review Registration and Search Strategy

This systematic review protocol was registered with PROSPERO (ID:CRD 42022339845) and follows the methodology of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Protocols (Moher et al., 2010). The PRISMA checklist can be found in Appendix A.
The search was completed on May 19, 2022, clwith inclusion criteria displayed in Table 1. The search strategy can be found in Appendix B. The search strategy included search terms on the older adult population, undergoing in-home positioning or monitoring systems as their intervention. Key words related to older adults included (“Aged” or “Senior” or “Over 65” or “Aging”) while terms on the setting included their home or house. For the technologies, terms included the purpose of monitoring (“Positioning” or “Localization”) and specific types of technologies including wireless trackers (Bluetooth, Wi-fi, Ultra-wide band, Zigbee), wearables (accelerometers, gyroscopes) camera and audio systems. The search did not include comparator group or outcomes to improve the sensitivity of the search. We included studies that had at least four patients to improve the sensitivity of the search.

Table 1: Inclusion and exclusion criteria

Abstract Inclusion Criteria	Full-Text Inclusion Criteria	Exclusion Criteria
Older Adults (65+)	All abstract inclusion criteria	Care centers (assisted living, long-term care, hospital etc)
Monitoring Technology		Conference Abstracts
In-home Setting		Reviews, Study Protocols
Sample size >4 patients	Positioning System	Non-English

Study Selection, Extraction and Quality Assessment

MEDLINE, EMBASE, CINAHL and Scopus were searched, and articles were de-duplicated. Abstract screening, full-text screening, data extraction and quality appraisal were completed by two reviewers, the first author (AC) and one of four secondary reviewers (SP, BC, LQ, JC). Reviewers were trained with 10 test abstracts and full-text articles and then concordance was reviewed. At each stage, inter-rater agreement was calculated using Kappa coefficient (McHugh, 2012). Disagreements were resolved by having both reviewers re-assess articles for two additional rounds, and then the article was discussed to reach a consensus.

Data extraction included article demographics (country, year published), study design (clinical, usability or technical study), population characteristics (age, gender distribution, clinical diagnoses, comparators), types of localization interventions (wearable or ambient, data transmission, technology readiness level, data analytics methods), outcomes (types of activities monitored, clinical assessments and outcomes, acceptability and reliability). Data was compiled into summary tables, presenting the population, technological intervention and clinical outcomes of each study.

To assess risk of bias, the JBI checklist for case series critical appraisal tool was used, as we did not expect any high quality randomized controlled trials related to in-home monitoring (Munn et al., 2020). Criteria for appraisal were pre-determined: studies with 7 or more ‘Yes’ ratings were considered high quality, studies with 4 to 6 ‘Yes’ ratings were considered moderate and studies with less than 5 ‘Yes’ ratings were considered low quality. No meta-analysis was planned as we did not expect to find high quality quantitative studies that would allow for heterogeneity to be assessed. Instead, the outcomes from each study were presented individually.

Clinical outcomes were summarized in summary statements, with only moderate or high-quality studies considered. Evidence was summarized as positive if the majority of studies showed positive results, and negative if the majority of studies showed negative results, and mixed if neither had a majority.

Results

Search Results

During the initial search, 1935 articles were found, with 1008 unique articles after de-duplication. After abstract screening, 127 articles remained, while after full-text screening, 46 articles were included in the final extractions, 36 considered technology-focused articles, and 10 articles that included relevant patient populations. Agreement between reviewers at the abstract screening stage was 94.9% with Kappa of 0.77, and agreement of 95.8% and Kappa of 0.71 for full-text screening. Quality assessment agreement was 76% with Kappa of 0.51. The PRISMA flowchart in Figure 1 maps out the excluded articles.

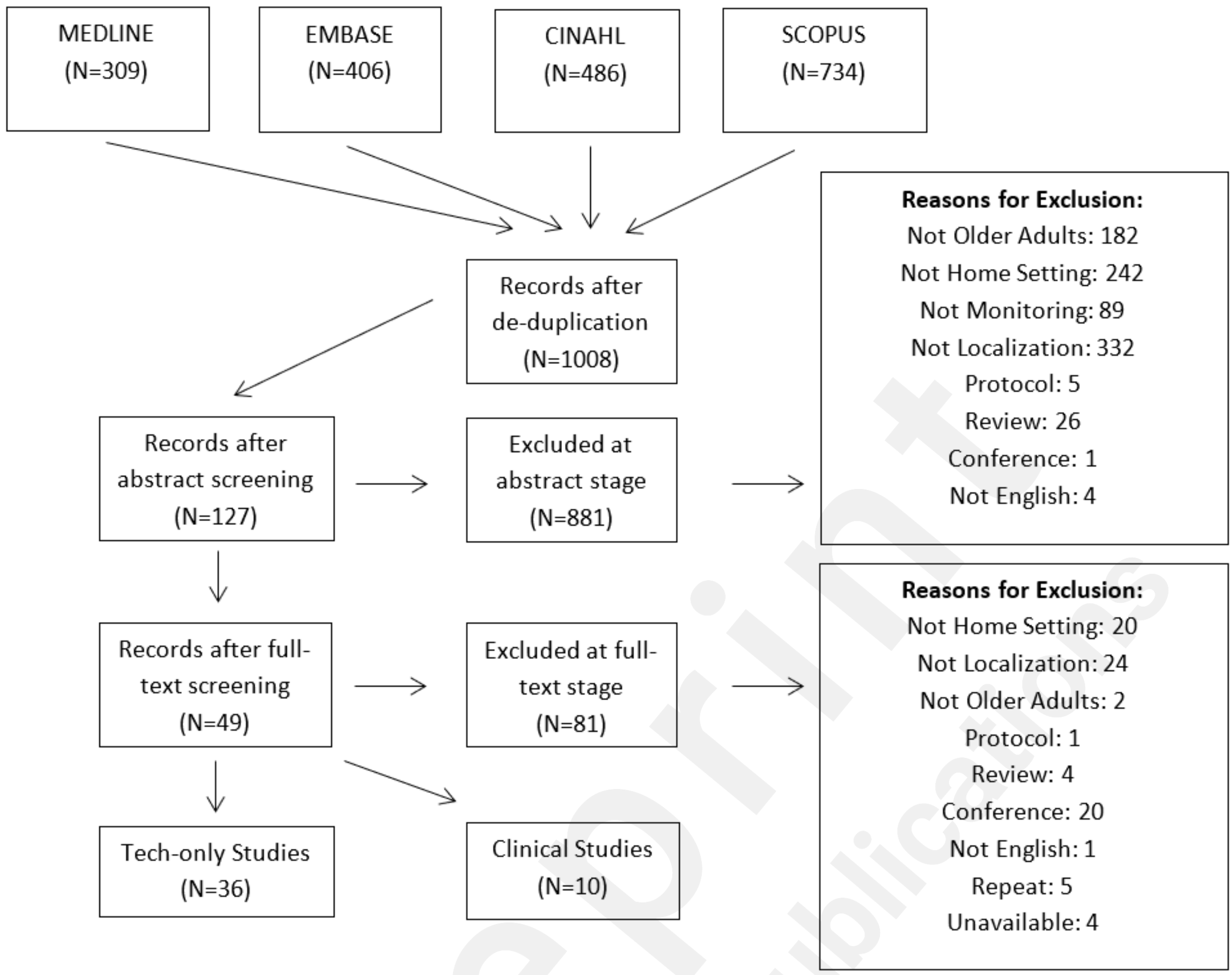

Figure 1 – PRISMA Flowchart showing included clinical studies (10) and technology-only studies (39)

Studies with Clinical Population

Table 2 displays the baseline characteristic for the ten papers that included relevant patient populations. Seven studies were conducted since 2019. Five studies were from North America, three in Europe and two in Asia. Two studies were descriptive studies of the technology, four studies had a mixed design and qualitative study design, two had qualitative study designs, one was a mixed study with qualitative and quantitative outcomes and one focused on quantitative outcomes. Only one study had more than 25 participants. Eight studies had more females than males.

All studies had patient populations that included older adults, though only seven specifically reported population characteristics. Four studies included older adults living at home with non-specific functional challenges, two focused on adults with mild cognitive impairment or dementia, one focused on older adults with frailty. Half of the studies (five) were considered low quality, three moderate and two high.

Table 3 shows the technologies and localization methods used in the included studies, their setting and the duration of monitoring. From a technology perspective, two used solely an ambient sensor design, five combined ambient sensors with wearables, and three used wearable-only designs. Ambient sensors included temperature sensors, magnetic door sensors, infrared motion sensors, light switch sensors, pressure detectors and LiDAR sensors. Wearables included inertial measurement units, ECGs, heart rate meters, and wearable wireless tags (Wi-Fi, Bluetooth Low Energy [BLE]). Of the ten studies, seven included technologies of unknown brand or model (three only used non-branded devices), while three listed the brands of devices used.

Most studies were done in the home setting (7/10, 70%), with two in a home-like lab setting and one in a lab setting. Studies in the lab-home involved monitoring sessions lasting between 1 hour and 7 days (Hung et al., 2021; Rahal et al., 2008; Tegou et al., 2019), while home-based monitoring ranged from 3 weeks to 18 months.

Table 4 displays the outcomes from studies that included patient populations. Seven included technical outcomes, six included usability and acceptability outcomes based on patient or clinician surveys or interviews, and three included clinical outcomes. Room detection accuracy ranged from 50-88% across three studies (Lach et al., 2019; Montoliu et al., 2020; Rahal et al., 2008), while one study reported failure rates of >15% for motion detectors and servers installed in the home (Hu et al., 2016). One study reported linear accuracies of 1.5-2.0m using wireless sensor networks within the home (Hung et al., 2021).

For studies that included usability and acceptability outcomes, surveys from three studies (Hu et al., 2016; Hung et al., 2021; Pais et al., 2020) showed positive results. One study focused on ease of setup of a smart home in a box design and found high ease of use, few concerns with devices, and highly efficient instructions (Hu et al., 2016). Another found highest satisfaction amongst older adults, followed by caregivers and lowest satisfaction with nursing staff (Pais et al., 2020). One study found an average System Usability Scale score of 62.8, indicating below average usability (Hung et al., 2021). Interview results from four studies (Chen et al., 2014; Lach et al., 2019; Rawtaer et al., 2020; Shin et al., 2021) found improved safety and security with devices but there was some perceived physical intrusiveness to ambient devices (Rawtaer et al., 2020) and some patients changed their behavior due to monitoring (Lach et al., 2019). One study found a tag-based system was highly acceptable (Chen et al., 2014).

Lastly, regarding clinical outcomes, one study provided qualitative observations on why patients behaved in certain ways in their home, finding certain activities are performed slower and some areas in the home are avoided including staircases to avoid falls, depending on their functional level (Shin et al., 2021). One study found no difference in behaviors between residents with mild cognitive impairment and those who were cognitively healthy, based on continuous monitoring of sleep and identifying frequency of forgetting to do activities (Rawtaer et al., 2020), while another study was able to classify patients as frail, pre-frail or non-frail with 80-87% accuracy using machine learning algorithms from Bluetooth-based wearable localization, being monitored for 1-7 days continuously in their own home while doing their own typical activities (Tegou et al., 2019).

Studies on Technology Validation

While the primary objective of this systematic review was to review the clinical evidence for in-home localization technologies to support in-home monitoring of older adults. We found 36 articles that reported that their technology would be used for localization of clinical populations. Table 5 is a summary of the characteristics of studies focused on developing and evaluating in-home localization technologies for older adults.

Studies on ambient sensors were from North America (3/6 studies, 50%), wireless tags were most studied in Europe (6/6, 100% for Bluetooth or Wifi, 5/7, 71% for other tags) and wireless tags alongside IMUs were solely studied in Asia (8/8, 100%). The majority of studies were from after 2016 (25/36, 69%). The stated purpose of monitoring was for older adults in a general sense in 27/36 (75%) of studies, while older adults with chronic diseases or disabilities were specified in 9/36 studies (25%). The purpose of monitoring was mostly for health and safety monitoring (21/36, 58%). The most common localization mode was to measure signal strength (23/36, 64%), followed by time-based localization (8/36, 22%) which calculates the time that it takes for a signal to travel from a tag to a reference point, and least commonly proximity sensing (5/36, 14%). Received signal strength involves estimating the distance between wearables and reference points based on the strength of the wireless signal. Localization accuracy was most reported as a linear distance (23/36, 64%), followed by classification of activities (13/36, 36%), room or area detection accuracy (6/36, 17%), and lastly

accuracy in detecting multiple people in a space (5/36, 14%).
Tables 6 summarizes the accuracies of different technologies, organized according to the method of localization, and the type of accuracy reporting. Ambient sensors included infrared sensors, radiofrequency transceivers, and video feedback. Devices were primarily used for detecting people passing through spaces, with accuracies of 79-98% in differentiating people, and 92% accuracy in detecting presence in a room.
Bluetooth and Wifi technologies can be used with either smartphones or individual tags, reducing the need for extra equipment for localization when compared to standalone tags. Accuracies ranged from 70-250cm, with room detection accuracies of 70-87%.
Localizer tags include radio frequency identification tags (RFID), ultra-wide-band (UWB) tags, Zigbee tags and global positioning system (GPS) tags. Linear accuracies were superior to Bluetooth or Wifi, ranging from 5-100cm, and area accuracies of 90%. Tags were also used for fall detection and object detection.
Combining localizers with inertial motion units (IMUs) allowed for a combination of activity classification and localization. Accuracies ranged from 7.6-189 cm across four modalities (UWB at 7.6cm, RFID at 10-40cm, Zigbee at 83-189cm and BLE at 47cm), while activity classification ranged from 89-100%, though reporting was not always clear on what activities were being classified. Area classification accuracies were between 86-90%.
Lastly, with unique technologies including sound-based technology, GPS, vibration sensors, pressure pads and triboelectric sensors, accuracies ranged from 20-30cm with activity recognition at 92-99%.

Summary Statements on Clinical Evidence for Localization

From the five moderate to high quality clinical studies, four studies reported on acceptability of in-home localization systems. Results were mixed, with two high quality studies indicating positive acceptability (Pais et al., 2020; Rawtaer et al., 2020), one finding below average usability (Hung et al., 2021), and one finding a range of concerns over device obtrusiveness (Lach et al., 2019).
Two studies reported on clinical outcomes from in-home localization systems. One high quality study showed no difference in behaviors between older adults with healthy cognition compared with mild cognitive impairment (Rawtaer et al., 2020) and one moderate quality study detected adaptive behaviors at home because of limitations to patient function (Shin et al., 2021).

Discussion

Principal Findings

This systematic review focused on the usage of localization methods to monitor older adults in their homes for any clinical application. While the primary objective was to evaluate the clinical evidence for localization technologies, a survey of technologies for in-home localization was also undertaken to understand upcoming technologies for localization.
Clinical utility of localization was mixed in this study. In the study by Rawtaer et al, cognitively healthy older adults (21 participants) and older adults with MCI (28 participants) were monitored and compared over 2 months using a custom set of motion sensors, proximity tags, a bed sensor and wearable to capture sleep, activity levels and forgetfulness in medications, keys or wallet. Amongst typical activities, there was no difference in behaviors (Rawtaer et al., 2020). A second study, examining frailty, used in-home localization to detect frailty by measuring number of transitions, speed of transitions and statistical features through machine learning algorithms, finding a classification accuracy of 82-85% when using random forest plots (Tegou et al., 2019). The model can be used in the future to detect frailty in the general population. The clinical evidence for using localization technology to support care of older adults is currently limited.
From an acceptability perspective, results were moderately positive (Hu et al., 2016; Hung et al., 2021; Lach et al., 2019; Pais et al., 2020; Rawtaer et al., 2020). Pais et al. (2020) discovered that

ambient sensors garner greater acceptance compared to wearables. Moreover, they noted that older adults and caregivers exhibit higher acceptance levels toward both technologies in contrast to nurses. This trend could be attributed to the necessity for monitoring daily performance issues among older adults and their families. Acceptability of home monitoring has been thoroughly studied previously, finding that the trade-offs are critical to consider when developing these technologies (Chan et al., 2022; Mann et al., 2001; Mihailidis et al., 2008; Pirzada et al., 2022). These findings align with the present systematic review, with obtrusiveness being a major detractor for these localization technologies balanced by improved safety and security.

Common technologies for localization include ambient sensors, Bluetooth or Wifi received signal strength, localizer tags using RFID, UWB, Zigbee, GPS or IMUs with localizers. This review also found unique localization devices including triboelectric trackers, ultrasound, floor vibration sensors and pressure pads. Highest linear accuracies were found with UWB technologies at 5-20cm compared with greater than 50cm for most other technologies. UWB uses time-based localization which involves measuring the time it takes for a signal to travel from a tag to a reference point and then trilateralize the signal. Room detection accuracies were comparable across technologies, ranging from 75-92% using Bluetooth, Wifi, RFID, radiofrequency transceivers, or Zigbee with IMUs .

The current literature is limited as it focuses primarily on technical measures of accuracy. The shift needs to be made towards localization for activity identification that can then be used as evidence to provide an intervention. UWB positioning has the potential to make the shift from where a patient is in the home at a room level to a furniture level that can then allow identification of activities. Further exploration and development of algorithms to automatically detect activities are required before broader clinical usage.

Comparison to the Literature

This systematic review fills an important gap by including clinical results, user acceptability and technological aspects of evaluating localization devices to support older adults to age-in-place. There remains little evidence for their usage for older adults, a finding that is supported by other systematic reviews. Lenouvel et al reviewed sensors to measure and support activities of daily living for older adults in 2019 (Lenouvel et al., 2020). While they did not focus on localization, they found passive and video sensor networks were used to assess ADLs across 13 studies out of their search of 10782 studies, finding that sensors could detect changes in activity patterns, but reported no clinical outcomes and finding only one study assessed acceptability of devices.

Another systematic review published in 2018 focused solely on technological aspects of human activity recognition supported with indoor localization. Ceron et al described common localization technologies and data fusion methods, reporting accuracy of activity detection and localization accuracies without consideration for age of participants (Ceron J. & Lopez D.M., 2018). Human activity recognition accuracy ranged from 72-99% across 27 studies, though the exact types of activities were not reported. Localization accuracies ranged from 0.8-7m, depending on the type of technology, though the type of technology was not reported in the review. These values are comparable to the present systematic review.

Strengths of Current Study and Recommendations for Future Studies

This systematic review had a strong search strategy, covering the major databases and having two reviewers screen, extract and assess quality of studies. Agreement between reviewers was high across screeners. The JBI quality assessment tool was used with a lower agreement with a Kappa of 0.51.

While the methodology of this review was strong, the findings were not. There is limited clinical evidence for using localization to support monitoring older adults. It was surprising that there were also few studies that evaluated the acceptability of monitoring technologies. Future studies need to translate these technologies into clinical and acceptability studies, identifying how technologies can lead to interventions that support aging-in-place. The quality of evidence also needs to be improved, with most studies having fewer than 25 subjects with a case study design and quality of studies being mixed. There are ample technologies that can be used for localization, but accuracy comparisons between studies is challenging because of the mix of ADLs being identified and the range of indoor spaces being localized. There needs to be clearer reporting of the spaces being monitored, accuracy of devices, and types of ADLs being monitored to allow comparability. Of upcoming technologies, UWB may be the most exciting, offering much higher accuracies than ambient sensors and more common wireless technologies like Wifi and Bluetooth.

The utility of localization techniques for health care is still untapped. While some initial work on detecting cognitive decline and frailty in the home setting has been documented in this review, further development and clinical evaluation of these technologies to determine potential use-cases still needs to be undertaken. Development of these technologies requires a multi-pronged approach that combines understanding the limits of the technology including the cost, the clinical applicability of localization for health management, and the acceptability of monitoring to enhance wellness. Technologies like Bluetooth, Wi-fi and IMUs are already well established in the market for various quality of life use-cases but not for health care.

Localization could be a powerful supporting tool for managing challenges with cognition, with interventions that take into account a user's living patterns, and reminders that are tailored to the home environment. Cognition, mental health, and frailty could be more accurately measured longitudinally, rather than relying on snapshot clinical assessment tools when combined with collecting information on self-care and in-home activity levels. There is great potential for localization technologies to support wellness in the home.

Conclusion

There is no evidence for the usage of in-home localization technologies for any clinical outcomes and mixed evidence for acceptability of localization technologies amongst older adults. However, there is a wide range of technologies available which have promising technical accuracies. The technology is ripe for monitoring devices to be tested clinically, providing data that can detect changes in cognition or frailty and drive interventions. Further study on the acceptability of these devices is also warranted to determine the least obtrusive and easier to use modalities that can bring the most benefit for older adults.

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Competing Interests

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Tables/Figures

Table 2: Baseline Characteristics from included clinical papers									
Author	Year	Country	Design Type	Subjects	Female	Age (Mean (SD) [Range]	Population	Category of Tech	Quality
Hu [1]	2016	USA	Mixed (Qualitative + Design)	13	62%	69.2 [54-85]	Older Adults	Ambient	Low
Rahal [2]	2008	Canada	Descriptive	14	71%	50 [22-73]	Mostly older adults	Ambient	Low
Shin [3]	2021	USA	Mixed (Qualitative + Design)	23	57%	73 (7.9) [62-89]	Older adults with difficulty conducting activities of daily living.	1. Wearable 2. Ambient 3. Wearable	Moderate
Pais [4]	2020	Switz.	Qualitative	21	48%	85 (7) [72-96]	Older adults living at home	1. Ambient 2. Wearable 3. Wearable	High
Lach [5]	2019	USA	Mixed (Qualitative + Design)	5	100%	86 (5.1) [70-90]	Older adults living alone in home	1. Wearable 2-5. Ambient	Moderate
Hung [6]	2021	Taiwan	Qualitative	8	60%	68 [64-77]	Adults with mild cognitive impairment or dementia	1. Wearable 2-3. Ambient	Moderate
Rawtaer [7]	2020	Singapore	Mixed (Qualitative + Quantitative)	49	67%	73 (5.3)	1. Cognitively healthy 2. Older adults with mild cognitive impairment	1-4. Ambient 5. Wearable	High
Montoliu [8]	2020	Spain	Descriptive	17	Not Reported	62.8 (12) [30-79]	Older adults	Wearable	Low
Chen [9]	2013	USA	Mixed	4	5**0%**	65 [46-81]	Range of	Wearable	Low

			(Qualitative + Design)				diagnoses (polio, multiple sclerosis, spinal cord injury)		
Tegou [10]	2019	Greece	Quantitative	271	56%	76.8 (5.2)	1. Non-frail 2. Pre-frail 3. Frail	Wearable	Low

Table 3: Technological Setup and Technical Accuracy of Localization Devices								
Author	**Year**	**Technology**	**Brand and Model**	**Localization Method**	**Purpose of Monitoring**	**Setting**	**Duration**	**Quality**
Hu [1]	2016	1. Temperature, Magnetic Door Sensor (2) 2. Motion Sensor (12)	Not Reported	Motion Detection Time	Not Reported	Home	9-10 weeks	Low
Rahal [2]	2008	1. Motion Sensor (10) 2. Tactile Carpet (18) 3. Light Switch (8) 4. Door Contact (48) 5. Pressure Detectors (1)	Not Reported	Motion Detection Time	Detect Walking or Preparing Sandwich	Lab Home	50 minutes	Low
Shin [3]	2021	1. Wristband: Heart Rate, Electrodermal Activity, Triaxial Accelerometer (1) 2. LiDaR (1) 3. Camera Wearable (1)	1. Empatica E4 2. FARO Focus S120 3. Not Reported	Camera-based	Functional Mobility, BADL, IADL	Home	18 months	Moderate
Pais [4]	2020	1. Ambient Sensors (Not Reported) 2. Activity Tracker (1) 3. ECG (1)	1. DomoCare 2. Not Reported 3. Preventice BodyGuardian	Passive IR sensor	BADL (toilet, fridge usage)	Home	12 months	High
Lach [5]	2019	1. Activity Tracker (1) 2. Motion Detectors (3) 3. Bed Pressure Sensor (1) 4. Chair Pressure Sensor (1) 5. Exit Sensor (1)	1. CamNtech MotionWatch 8 2. Alarm.com BeClose	Motion Detection Time	Functional Mobility, BADL (Kitchen, bathroom activity), Sleep Quality	Home	3 months	Moderate
Hung [6]	2021	1. Bluetooth Localizer (4) 2. NFC scanner voice-guided exercise 3. Voice Questionnaire	Not Reported	Signal Intensity	Cognitive Training	Lab	5 weeks (Intermittent) 60 minute sessions	Moderate
Rawtaer [7]	2020	1. Passive Infrared Sensor (4) 2. Proximity Tags (1) 3. Medication Box (1) 4. Bed Sensor (1) 5. Pedometer, Heart Rate Meter (1)	1-4. Not reported 5. Microsoft Band	Motion Detection	Identify mild cognitive impairment or healthy cognition in community-	Home	2 months	High

					dwelling seniors			
Montoliu [8]	2020	1. Smartwatch (GPS, gyroscope, accelerometer, compass, ambient light sensor) (1) 2. Wi-Fi (Wireless Access Point) (2)) 3. Bluetooth Low Energy Beacon (3) 4. Personal phone (varying)	1. Sony Smart Watch 3 2. Not Reported 3. iBKS	Signal Intensity (RSSI)	Localization to detect behavioural changes	Home	2 months	Low
Chen [9]	2013	1. Wifi Tag (1) 2. Wireless Access Points (3-7) 3. GPS Logger	1-2. Ekahau T301A 3. iBlue 860E	Signal Intensity (Fingerprinting), GPS	The complete measure of physical activity using various sensors	Home	3-6 weeks	Low
Tegou [10]	2019	1. Smartphone (1) 2. Bluetooth beacons (5)	1. LG Nexus 5x 2. Sensoro	Signal Intensity (RSSI)	Identify frailty in community-dwelling adults	Home	1-7 days	Low

Table 4: Outcomes from Studies that included Patient Populations

Author	**Year**	**Category of Tech**	**Outcomes Measured**	**Technical Outcomes**	**Qualitative Outcomes**	**Clinical Outcomes**	**Quality**
Hu [1]	2016	Ambient	**Survey:** ease of installation, acceptability of sensors, instructions efficiency Device failure rates	Failure Rate: <15%, motion detector, temperature sensors >15%: door sensor, server, relays	Ease of use: 2.9/4, High Concerns with devices: 1.6/5 Low concerns Instructions efficiency: 80.95% Yes	N/A	Low
Rahal [2]	2008	Ambient	Localization accuracy	Combined: 85% room detection accuracy Accuracy for each device: 1. 88% 3. 50% 4. 77% 2, 5. Not Measured	N/A	N/A	Low
Shin [3]	2021	Ambient and Wearable	**Patient interviews:** Adaptive behaviours at home	N/A	For difficult activities, patients most often give up on them or perform slowly. Home adaptations are rarely implemented due to cost.	N/A	Moderate

					High fall risk locations are avoided.		
Pais [4]	2020	Ambient and Wearable	**Survey:** satisfaction with devices	N/A	Ambient sensors: Older adults: 81.6% positive Caregivers: 80.0% positive Nurses: 69.0% positive Wearable sensors: Older adults: 72.2% positive Caregivers: 60.0% positive Nurses: 49.0% positive	N/A	High
Lach [5]	2019	Ambient and Wearable	Measurement of activity levels and Sleep duration **Patient Interviews:** Patient experiences with monitoring	Activity: Self-reported activity and sensor activity correlate. Actigraphy did not. Sleep: Self-reported: 492 mins Actigraphy: 524 mins Bed Sensor: 435 mins	Interview: Opinions ranged widely on how noticeable and bothersome ambient sensors were. Behaviours sometimes changed due to monitoring presence. Compromises to data due to the presence of others in the home is a concern	N/A	Moderate
Hung [6]	2021	Ambient and Wearable	Linear localization accuracy **Patient survey:** system usability **Physician survey:** availability and quality of system	1.5-2.0m in 48 x 32m space	Patients: System Usability Scale: 62.8±11 (out of 100) Physicians: Cognitive training more targeted and realistic in patients' home	N/A	Moderate
Rawtaer [7]	2020	Ambient and Wearable	**Patient interviews:** purpose not specified **Clinical:** Comparison between healthy cognition and mild cognitive impairment	N/A	83% positive feedback. Improved safety, security, some intrusion where sensors were setup	No difference in behaviours between healthy cognition and mild cognitive impairment	High
Montoliu [8]	2020	Wearable	Localization accuracy	Room Detection Accuracy: 50.9-53.8%	N/A	N/A	Low

Chen [9]	2013	Wearable	Localization accuracy **Patient interviews:** Acceptability of system	Room Detection Accuracy: 62-87%	Lightweight tag, little effort is needed when using tags. The inclusion of GPS is helpful.	N/A	Low
Tegou [10]	2019	Wearable	**Clinical:** Identify frailty in community dwelling adults	N/A	N/A	Accuracy in classifying frailty: 80-87%	Low

Table 5: Characteristics of Studies Focused on Monitoring Technologies

Category	**Subcategory**	Ambient (Video, Infrared, Magnetic, Pressure)	Bluetooth or Wifi	Localizer Tag (RFID, UWB, Zigbee, GPS)	IMU and Localizer	Other	Total
Total Number of Articles		6	6	7	8	9	36
Continent	Europe	1	6	5		1	13
	Asia	1		1	8	3	13
	North America	3				5	8
	Oceania	1		1			2
Year	Pre-2010		1			1	2
	2010-2016	4	1		3	1	9
	2016-2022	2	4	7	5	7	25
Target Audience	Older Adults	4	4	6	7	6	27
	Chronic Disease	2		1	1	3	7
	Disabilities		2				2
Purpose of Monitoring	Indoor Localization	3		1	1		5
	Activity Detection	1			3	2	6
	Health/ Safety Monitoring	2	3	5	4	7	21
	Self-Care		3	1			4
Localization Mode	Signal Strength	2	6	5	7	3	23
	Proximity Sensing	4	1			3	5
	Time-based Localization			2	1	2	8
Accuracy Reporting	Distance	2	3	6	6	6	23
	Activity Classification	2		2	5	4	13
	Room/Floor/ Area Detection	1	3		2		6
	Multiple	3		1		1	5

	Tag/Person Detection						

Table 6: Accuracy Reporting from Localization Technologies

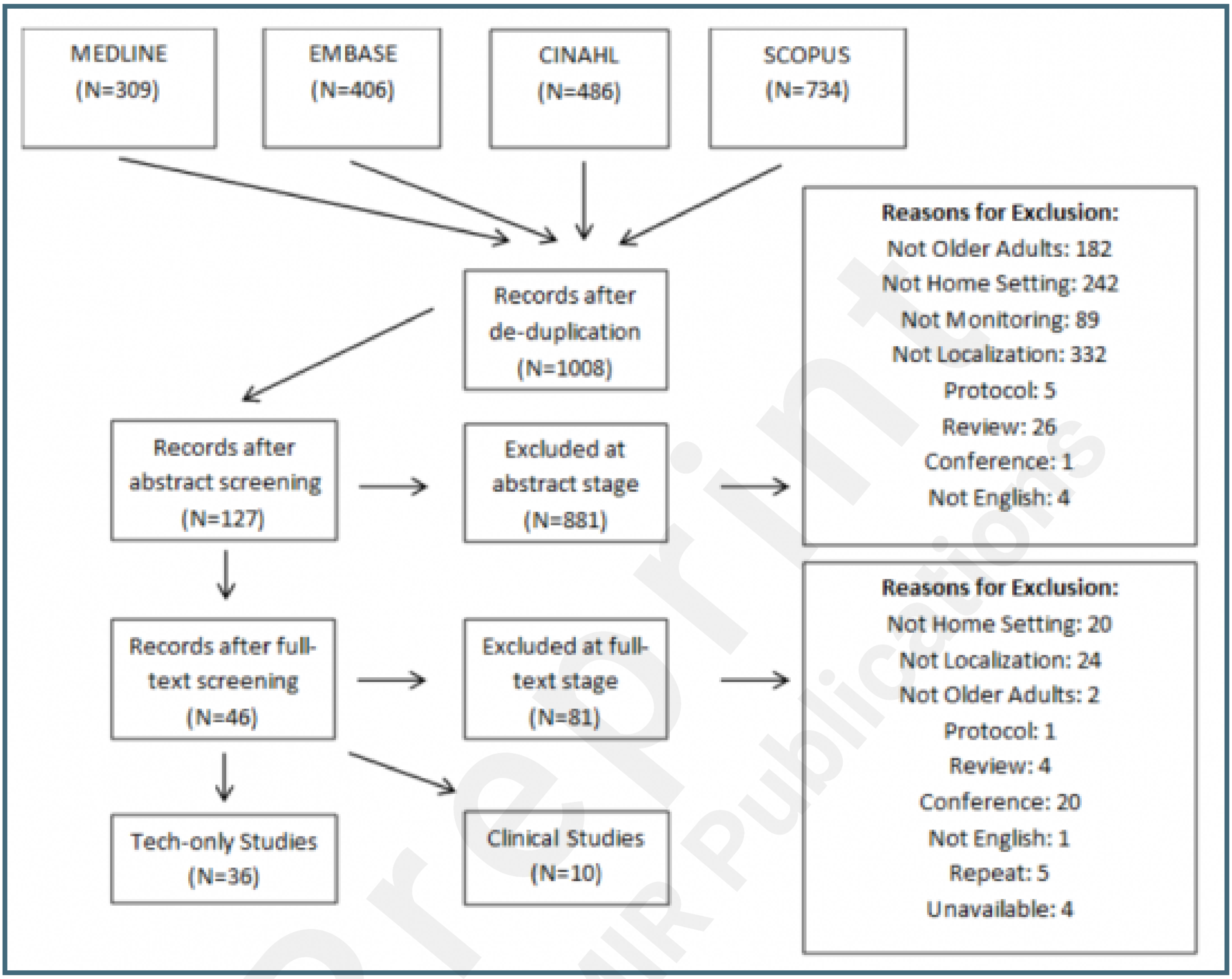
	Distance	Activity Classification	Room/Floor/Area Detection	Multiple Tag/Person Detection
Ambient (Video, Infrared, Magnetic, Pressure) **6 Studies**	Studies: 1/2 (50%)	Studies: 2/2 (100%)	Studies: 1/1 (100%)	Studies: 3/3 (100%)
	Thermopile Sensor: [11] 12-65cm Infrared Sensors: [12] Not Reported	RF Transceiver: [13] Walking: 97%, Standing: 95% Video: [14] Sensor Placement Optimization: 98%	RF Transceiver: [13] Room Detection: 92%	RF Transceiver: [13] >1 Person: 79-90% IR and RF Transceiver: [15] 2 Males: 83% vs 1 Male, 1 Female: 98% Infrared Doorway Sensor: [16] One person: 89%, Two people: 81%
Bluetooth or Wifi **6 Studies**	Studies: 4/4 (100%)		Studies: 3/3 (100%)	
	Wireless Sensor Network: [17] <250cm Bluetooth: [18] 60-300cm [19] 70-240cm, [20] 86cm		Bluetooth: [18] Area Accuracy (1m x 1m): 95%, [21] Room Detection Accuracy 75-84% Wifi: [22] Room Detection Accuracy: 70-87%	
Localizer Tag (RFID, UWB, Zigbee, GPS) **7 Studies**	Studies: 5/6 (83%)	Studies: 2/2 (100%)	Studies: 1/1 (100%)	Studies: 1/1 (100%)
	RFID: [23] 17cm, [24] Not Reported UWB: [25] 5cm, [26]:5-20cm Zigbee: [27] 92cm UWB+BLE [28]: 23-100cm	UWB: [26] Fall Detection: Sensitivity 99%, Specificity 98% RFID: [29] Object Identification 88%	RFID: [23] Area Accuracy (1.1m x 1.2m): 90%	RFID: [29] Multi-Tag Sensitivity 76-90%
IMU and Localizer **8 Studies**	Studies: 6/6 (100%)	Studies: 5/5 (75%)	Studies: 2/2 (100%)	
	IMU+UWB: [30] 7.6 cm IMU+RFID: [31] 10-40cm in 3.6 x 2.8m, [32]<50cm IMU+Zigbee: [33] 120cm in 11 x 5.75m, [34] 83-189cm IMU+BLE: [35] 47cm	IMU+Zigbee: [33] Fall Detection: 89%, [36] Unspecified Activity: 100% IMU+RFID: [32] Posture Recognition: 100% IMU+BLE: [35] Step count within 1 step/minute IMU+BLE [37]: Activity	IMU+Zigbee: [36] Area Accuracy (2x2m): 90% IMU+BLE: [37] Room Detection Accuracy 86.6%	

		Classification: 95.0%		
Other **9 Studies**	Studies: 5/6 (83%) Triboelectric Tracker [38]: At 1.5m, 20-30cm Unspecified Doorway Sensors: [39] Distance Traveled Error: 10.5-24% Android Location-based Service: [40] Not Reported Ultrasound+RF: [41] 11cm Floor Vibration Sensor: [42] 24-61cm BLE+Acoustic+Light Fidelity: [43] 20cm	Studies: 3/4 (75%) IMU+Mic+Wifi: [44] ADL Recognition: 92-99% Unspecified Doorway Sensors: [39] Activity Detection: 92% Ultrasound+RF: [41] Gait Speed Error: 91%, Distance Walked: 92% Floor Vibration Sensor: [42] Footstep Detection: 95-99% Ambient+Scales+IMU: [45]: Not Reported		Studies: 0/1 (0%) IR+Pressure Pad+RF Transceiver: [46] Not Reported

Supplementary Files

Figures

PRISMA Flowchart showing included clinical studies (10) and technology-only studies (36).



CONSORT (or other) checklists

PRISMA Checklist.
URL: http://asset.jmir.pub/assets/595cd5d7088a954355f4657a65d958cd.pdf