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REVIEW ARTICLE

Literature review on monitoring technologies and their outcomes in independently living elderly people

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Abstract

Purpose: To obtain insight into what kind of monitoring technologies exist to monitor activity in-home, what the characteristics and aims of applying these technologies are, what kind of research has been conducted on their effects and what kind of outcomes are reported. *Methods*: A systematic document search was conducted within the scientific databases Pubmed, Embase, Cochrane, PsycINFO and Cinahl, complemented by Google Scholar. Documents were included in this review if they reported on monitoring technologies that detect activities of daily living (ADL) or significant events, e.g. falls, of elderly people in-home, with the aim of prolonging independent living. *Results*: Five main types of monitoring technologies were identified: PIR motion sensors, body-worn sensors, pressure sensors, video monitoring and sound recognition. In addition, multicomponent technologies and smart home technologies were identified. Research into the use of monitoring technologies is widespread, but in its infancy, consisting mainly of small-scale studies and including few longitudinal studies. *Conclusions*: Monitoring technology is a promising field, with applications to the long-term care of elderly persons. However, monitoring technologies have to be brought to the next level, with longitudinal studies that evaluate their (cost-) effectiveness to demonstrate the potential to prolong independent living of elderly persons.

➤ Implications for Rehabilitation

- Insight was obtained of what kind of technologies exist to monitor activity of daily living, what their functionalities and outcomes of using these technologies are to prolong independent living of non-institutionalised elderly people.
- Five main groups of monitoring technologies exist with a wide range of functionalities. Research into the use of monitoring technologies is widespread but in its infancy, consisting mainly of small-scale studies and including few longitudinal studies.
- Research into the use of monitoring technologies demonstrated that the systems are able to monitor daily activities and have the potential of prolonging independent living of elderly people.

Keywords

Activities of daily living, fall events, functional health status, prolonging independently living, posture recognition

History

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Introduction

Solutions are needed to cope with the complex care demands of aging, and to satisfy the needs of elderly persons to live as long as possible in their own homes. This is necessary, since the growing number of elderly people, e.g. in the Netherlands, places a substantial demand on healthcare services. Age is, for example, an important risk factor in the development of chronic disorders, multi-morbidity and disorders such as Alzheimer's disease. In addition, the elderly have an increased risk of falling and of sustaining hip fractures [1,2]. However, resources to deal with this complex care demand are becoming scarce [3,4]. Through advances in sensor and telecommunication technology, monitoring technology may become one of the key solutions for achieving a more efficient healthcare system and allowing elderly people to live longer independently [5,6]. This review focuses on the daily activity of elderly people at home, since immobility or a general reduction in their functional health may lead to or be caused by disease, and may jeopardise their independence and well-being [7,8].

In 1995, Celler et al. presented the first telemonitoring system that could determine remotely the functional health status of elderly people, by continuously and passively monitoring interactions between elderly people and their living environment over long periods of time. To accomplish this, activity monitoring used magnetic switches in doors that record movement between rooms, infrared sensors on the walls that identify activity in specific areas of the room and sound sensors that determine the type of activity.

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With this development, it became possible to respond earlier to activity changes, and thus changes in functional health status; monitored activity would be compared to the ''normal'' activity patterns of the elderly person, and activity changes would be noted. The use of monitoring technology may therefore allow for timely and well-targeted interventions that can intercept potential crises [7].

Several other monitoring technologies emerged in subsequent decades that could detect daily activity, changes in health status or injury, e.g. fall detection. However, an overview of the systems that exist to monitor activity is lacking; so too is an overview of their functionalities, and of the outcomes of using these monitoring technologies in the home environments of non-institutionalised elderly people. These insights would be valuable, as knowledge is needed about available and appropriate interventions to deal with the growing complex care demands of elderly people as well as the scarcity of resources with which to do so. Therefore, a systematic electronic document search was performed, guided by the research question: What types of technologies exist to monitor the activity of non-institutionalised individuals in the home environment; what are their characteristics, aims, applications and study characteristics, and what is known about the outcomes of using monitoring technologies to detect activities of daily living?

Methods

Search strategy

An electronic document search was conducted in the scientific databases Pubmed, Embase, Cinahl, Cochrane and PsycINFO. This search was complemented by a search using Google Scholar for conference publications and journal articles. The search using Google was restricted to the first 160 hits.

Key terms

The following key terms were used in combination in the database search: (''activities of daily living'' [MESH], ''aged'' [MESH] and ''independent living'') and ''gerontechnology'' or ''smart home'' or ''ambient assisted living'' or ''sensor motion detection'' or ''domotic*'' or ''in-home monitoring''. The search focused on documents where the key terms were in the title or abstract. The key terms were used as free text words in Google Scholar.

Inclusion and exclusion criteria

Articles were included when they reported on monitoring technologies addressing in-home detection of activities of daily living (ADL), significant events, e.g. falls, or changes in health status of independently living elderly people, with the aim of prolonging independent living. Articles were excluded when they focused on monitoring vital signs for disease management in elderly people. Articles were subsequently excluded when they had no links to the identification of daily activities or focused only on environmental control. Finally, inclusion was restricted to English, German or Dutch articles.

Study selection

The list of retrieved titles was first filtered by removing duplicates. The remaining titles were assessed by two reviewers according to the selection criteria. Agreement between the reviewers for each title and abstract was calculated with Cohen's kappa [9]. Titles meeting the criteria received two points. Titles not meeting the criteria received zero points and, when there was doubt, one point was given. Thereafter, abstracts were assessed when the sum scores of their corresponding titles equalled two or more points. Again, abstracts received zero, one or two points, in accordance with the selection criteria. Disagreement was solved by discussion.

Data extraction

When the sum score of an abstract equalled two or more points, the full article was retrieved and scanned in order to determine the characteristics of the identified monitoring technology, the aim of using the monitoring technology, study characteristics and reported outcomes.

Characteristics of monitoring technology

For each article, first the type of monitoring technology was identified. Then, the full articles were grouped according to corresponding monitoring technologies, for further analysis.

Aim of monitoring technology

For each article, the aim of using the identified monitoring technology was established. A single identified monitoring technology may include more than one aim.

Study characteristics

For each article, the type of study design that was applied was established. The articles were grouped into seven categories, namely: longitudinal studies (randomised controlled trials, cohort studies), pilot studies, case studies/reports, activities performed in a laboratory setting, testing of the monitoring algorithm on a dataset, qualitative research and descriptive articles. Articles were grouped according to their methodological sections.

Outcomes

In addition, study outcomes in terms of (cost-) effectiveness, system functionality and responses of end users were extracted.

Results

The electronic document search yielded 942 references after duplicates were removed. The Cohen's kappa for agreement between the two reviewers was 0.465 (KP, LH). Subsequently, two reviewers (KP, CW) assessed the remaining 342 abstracts according to the inclusion and exclusion criteria and concluded that a total of 161 articles were eligible for full article assessment. Twenty articles were subsequently excluded as they did not meet the inclusion criteria or described a review. A total of 141 full articles were selected for full text analysis (Figure 1).

Five main groups of monitoring technology

Analysis of the 141 full articles revealed five main types of monitoring technology, namely: in-home passive infrared motion sensors ($N = 61$), body-worn sensors ($N = 26$), video monitoring ($N = 8$), pressure sensors ($N = 3$) and sound recognition ($N = 2$).

Furthermore, nine articles described a smart home setting and 31 articles described a multicomponent technology, e.g. the use of body-worn sensors together with PIR motion sensors and video monitoring [119]. One article described the use of aluminium foil as a fall sensor and it was not possible to assign this technology to one of the previous mentioned groups [148].

Analysis revealed three main aims in applying monitoring technology, namely: detection of (ADL) activities, of significant events e.g. falls, and of changes in health status. In several articles, monitoring technology was used for multiple purposes.

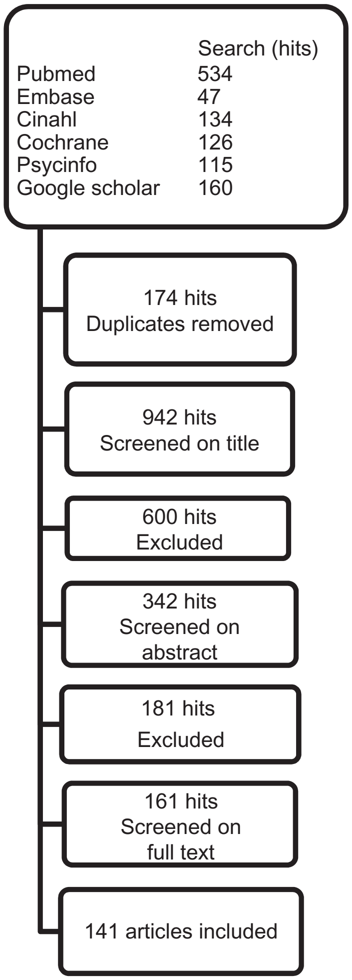

Figure 1. Flow diagram.

Thus, these main aims of monitoring technology may be combined.

Below the five main types of monitoring technologies are described; a separate section is devoted to the use of smart homes, multicomponent monitoring technologies and aluminium foil as a fall sensor.

Passive infrared motion sensors

In total, 61 articles [7,8,10–68] described the use of passive infrared (PIR) motion sensors to detect the activity of individuals (Table 1). PIR motion sensors are placed on walls or ceilings in the home of the elderly person and automatically and continuously collect data about predefined activities within the home [7]. PIR motion sensors are heat-sensitive and detect the presence of residents in rooms through changes in temperature. There are also subgroups of PIR motion sensors that can detect specific types of activity, including sensors to measure stove use, room temperature, water use or opening of cabinets, windows or doors. Sensor data is collected and transmitted to caregivers by a base station. The data is interpreted and subjected to trend analysis to detect changes in daily activity and accompanying potential changes in health status. As a result, it is possible to recognise patterns in daily activity and to generate alerts if deviations occur [8].

Aim of monitoring

PIR motion sensors are mainly used to detect the degree of activity and the performance of ADL activities inside the home ($N = 43$), to detect falls or other significant events ($N = 9$) and to detect changes in health status ($N = 10$). Other aims are detecting (ADL) activity in order to identify changes in health status ($N = 8$) or to recognise significant events such as falls ($N = 2$). In most cases, monitoring technologies combined more than one aim, e.g. detection of (ADL) activity together with detection of significant events (Table 1).

Gait velocity ($N = 4$), localisation ($N = 3$), time out of home ($N = 1$), sleep patterns ($N = 1$) and night-time activity ($N = 1$) can also be detected with PIR motion sensors.

Study characteristics

In total, six articles focused solely on describing the PIR motion sensor technology. The use of PIR motion sensor technology was validated in 13 articles through testing the algorithm or total system by simulating falls and/or activities in a laboratory setting, or through testing the algorithm on existing datasets. Twenty-four articles described case studies, including a maximum of three persons who were monitored for periods ranging from 7 days to one-and-a-half years (Table 1). Eleven articles focused on pilot studies testing the use of PIR motion sensor technology within samples of more than three persons for periods ranging from 51 days to 2 years. In addition, the long-term use and effects of monitoring technology was described in four articles, with two articles describing the results of a cohort study with a monitoring duration of about 3 years. One article described a randomised controlled trial with a duration of 2 years of monitoring, and one article described an implementation study that also had a duration of 2 years of monitoring. Two articles described the results of qualitative studies. Two articles included more than one study design: (1) focus groups followed by a pilot study and (2) testing the algorithm on an existing dataset followed by a pilot study.

Outcomes

Research regarding the use of PIR motion sensors focused mainly on demonstrating their functionality in terms of accuracy rate (Table 1). Accuracy of monitoring ranged from 25% to 100%. In several articles, different algorithms were compared to each other in terms of accuracy. Error rates were given; they ranged from 1.1% to 25%. Sensitivity and specificity were only described in one article. In addition, functionality was demonstrated through more general outcome measures, by showing activity reports or other outputs, in 33 articles. In six articles, more qualitative outcomes such as acceptance by the resident or caregiver, influence on stress levels or reasons for using monitoring technology were presented. Improvements in efficiency, willingness to pay for the system and cost were studied in only 2 out of 62 articles that described the use of PIR motion sensors.

Body-worn sensors

Twenty-six articles described the use of wearable sensor technology to detect the activity and posture of individuals [69–94]. Body-worn sensor systems have the ability to measure activity and mobility directly, as they are positioned on the trunk, on limbs or in clothes, e.g. in a belt. Accelerometers ($N = 20$) are the most frequently used technology to measure activities, such as standing, sitting, bending or falling. Accelerometers can be positioned on the trunk, waist or hearing aid; they detect activity by measuring (linear) accelerations in bodily movements [88].

Aim of monitoring

Accelerometers are mainly used to detect the degree of activity and the performance of ADL activities ($N = 13$), or to detect falls or other significant events ($N = 12$). Body-worn sensors are also

Table 1. Summary of passive infrared motion sensor technology.

References	Author (year); country	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[7]	Celler et al. (1995); Australia	Detecting (ADL) activity to identify changes in health status.	Description of technology.	–	–	Google Scholar	Journal
[8]	Glascock & Kutzik (2006); USA	Detection of (ADL) activity.	(1) Pilot study at 2 field sites; N = unknown; 6 months of monitoring; (2) Pilot study; $N = 26$; 12 months of monitoring.	Yes	98% reliability; 95% machine validity; accepted by participants and caregivers.	Google Scholar	Journal
[10]	Alwan et al. (2005); USA	Detection of (ADL) activity.	Case study $N = 1$; 37 days of monitoring; Compare monitoring data against PDA.	No	High false detection proportions by system; microwave and stove sensors not significant different in reliability compared to cabinet sensors.	Google Scholar	Journal
[11]	Austin et al. (2011a); USA	Detection of gait velocity.	Cohort $N = 20$ in multiperson residences; 3 years of monitoring.	No	Accuracy: correlation means GMM and clinical assessment 0.877 ($p < 0.0001$), 95% BI (0.79, 0.94).	Pubmed	Journal
[12]	Austin et al. (2011b); USA	Detection of gait velocity.	Case report $N = 2$ out of cohort $N = 20$ [Austin (2011b)]; 3 years of monitoring.	No	Method applicable for detecting abrupt changes in gait function (e.g. from 70 cm/s towards 40 cm/s after stroke) and long-term changes over time.	Embase	Conference proceeding
[13]	Bamis et al. (2008); USA	Detection of (ADL) activity, changes in health status, significant events, localization.	Case study residence A ($N = 1$); 7 months of monitoring; residence B ($N = 3$) 4 months of monitoring.	No	Functionality demonstrated of system to detect activity and deviations in activity patterns.	Google Scholar	Conference proceeding
[14]	Bamis et al. (2010); USA	Detection of (ADL) activity, changes in health status, significant events, localization.	Case study residence A ($N = 1$); 7 months of monitoring; residence B ($N = 3$) 4 months of monitoring.	No	Functionality demonstrated of system to detect activity and deviations in activity patterns.	Google Scholar	Journal
[15]	Barger et al. (2005); USA	Detection of (ADL) activity.	Case study $N = 1$; 65 days of monitoring.	No	Low classification uncertainty system to detect behavioural patterns.	Google Scholar	Journal
[16]	Celler, B (1996); Australia	Detecting (ADL) activity to identify changes in health status.	Pilot study $N = 4$; 5 months of monitoring.	No	Technical functionality demonstrated to monitor functional health status.	Google Scholar	Conference proceeding
[17]	Chen & Nugent (2009); UK	Detection of (ADL) activity.	Testing scenario ontology-based approach on dataset.	No	Functionality demonstrated.	Google Scholar	Journal
[18]	Cook & Schmitter-Edgecombe (2009); USA	Detection of (ADL) activity.	Testing algorithm in laboratory setting ($N = 60$).	No	Accuracy: 91% accuracy (naïve Bayesian algorithm); Accuracy 98% (Markov Models); 24% error dataset anomalous; 4–25% of simulation based activities erroneous.	Pubmed	Journal

[19]	Dalal et al. (2005); USA	Detection of (ADL) activity and significant events.	Case study $N = 1$; 37 days of monitoring. Compare monitoring data against PDA.	No	κ correlation algorithm – PDA (only main meals) 0.84, Sens 91%, Spec. 100%; κ correlation algorithm – PDA including coffee and snacks: 0.67, Sens 92%, Spec. 74%.	Google Scholar	Conference proceeding
[20]	Demongeot et al. (2002); France	Detection of (ADL) activity and fall events.	Description technology.	–	–	Pubmed	Journal
[21]	Fernández-Llatas et al. (2011); Spain	Detecting (ADL) activity to identify changes in health status.	Description technology.	–	–	Pubmed	Conference proceeding
[22]	Franco et al. (2010); France	Detecting (ADL) activity to identify changes in health status.	Case study $N = 1$; 49 days of monitoring.	No	Functionality system demonstrated.	Google Scholar	Conference proceeding
[23]	Glascock & Kutzik (2000); USA	Detection of (ADL) activity.	Case study $N = 1$; 13 days of monitoring.	No	Functionality monitoring system to monitor and differentiate between different activities; trend analysis.	Google Scholar	Journal
[24]	Hagler et al. (2010); USA	Detection of gait velocity.	Performing simulated activity in laboratory setting $N = 27$.	No	Average measured walking speed of 102 cm/s; system average error of less than 7% without calibration and 1.1% with calibration.	Pubmed	Journal
[25]	Hayes et al. (2004); USA	Detecting (ADL) activity to identify changes in health status.	Pilot study $N = 3$; 8 weeks of monitoring.	No	Approach is practical and effective for estimating walking speed over time and detects any variation.	Pubmed	Conference proceeding
[26]	Hayes et al. (2007); USA	Sleep patterns.	Pilot study $N = 14$; 6 months of monitoring.	Yes	Functionality system demonstrated. Coefficient of variation of hours in bed sign. higher in MCI group compared to healthy individuals.	Google Scholar	
[27]	Hayes et al. (2008); USA	Detecting (ADL) activity to identify changes in health status.	Pilot study $N = 14$; 6 months of monitoring.	Yes	Functionality system demonstrated: variation coefficient median walking speed mild cognitive impairment (MCI) group (0.147 ± 0.074) twice as high compared with healthy group (0.079 ± 0.027; $t_{11} = 2.266$, $p < 0.03$). Day-to-day pattern of activity of subjects in the MCI group was more variable.	Pubmed	Conference proceeding
[28]	Johnson (2009); USA	Detection of (ADL) activity to identify significant events.	Qualitative study $N = 29$ users and $N = 30$ informal caregivers.	Yes	Advantages: peace of mind, for users and family; efficiency and non-invasive nature. Disadvantages: cost, alarms when on holiday, lag time between fall and notification.	PsycINFO	PHD thesis

(continued)

Table 1. Continued

References	Author (year); country	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[29]	Kaushik & Celler (2007); Australia	Detecting (ADL) activity to identify changes in health status.	Performing simulated activity in laboratory setting $N = 11$.	No	Dead points with low detection sensitivity and hence raising false alarms Multiple sensors increase sensitivity of even small movements.	Google Scholar	Journal
[30]	Kaye et al. (2010); USA	Detection of (ADL) activity, gait velocity, time out of home.	Cohort $N = 233$; 33 months of monitoring.	No	Feasibility sensors demonstrated to detect walking speed, leaving home, computer use.	Google Scholar	Journal
[31]	Le et al. (2007); France	Detection of (ADL) activity.	Description technology.	–	–	Pubmed	Conference proceeding
[32]	Le et al. (2008); France	Detection of (ADL) activity.	Case study $N = 2$; 31 days of monitoring.	No	Functionality system demonstrated: recognition rules work to detect activities.	Pubmed	Conference proceeding
[33]	Lee et al. (2007); Korea	Detection of (ADL) activity and changes in health status.	Pilot study $N = 9$; 3 months of monitoring.	No	Average error ratio 13.4%; Usability according caregivers: overall convenience system not bad, want more secure access, easier layout, ground plan elder's house, SMS service, index for current status.	Google Scholar	Book chapter
[34]	Liao et al. (2011); UK	Detection of (ADL) activity.	Testing on existing dataset from MIT laboratory $N = 1$; 2 weeks of monitoring.	No	Classification accuracy 88.2%.	Pubmed	Journal
[35]	Litz & Gross (2007); Germany	Detection of significant events and changes in health status.	Description technology.	–	–	Google Scholar	Book chapter
[36]	Lotfi et al. (2011); UK	Detection of (ADL) activity and changes in health status.	Case study $N = 2$ dementia patients; first case 20 days of monitoring; second case 1.5 year of monitoring.	No	System usable to identify abnormal behaviour; overall functionality system demonstrated to identify health status.	Google Scholar	Journal
[37]	Mahoney et al. (2008); USA	Detection of (ADL) activity.	Pilot study $N = 19$ caregivers; 6 months of monitoring.	No	Positive results worker morale, productivity. Reduction caregiver stress; easy to learn and use; not intrusive or isolating; WTP informal caregivers \$10–130 depending on features.	PsycINFO	Journal
[38]	Mahoney et al. (2009); USA	Detection of (ADL) activity.	Mixed methods approach: focus groups $N = 26$; pilot $N = 29$ (10 residents, 10 family members, 9 staff); 4 months of monitoring on average.	No	Reasons for using monitoring system: worries about safety, well-being residents. Memory-related: medication, meals, shutting off toilet/bath water (building staff); Families: system easy to use and satisfied. WTP	Google Scholar	Journal

					per month max $60. System feasible to monitor activity.		
[39]	Martin et al. (2007); UK	Detection of (ADL) activity.	Qualitative study $N=7$ in staff of community-based dementia patients	No	Positive perception and acceptance: support their work, risk management without constant physical intrusion. Difficult to identify falling. For care requirements useful: sleep pattern, water usage, front door activity, general activity.	Cinahl	Journal
[40]	Monekosso & Remagnino (2009); UK	Detection of (ADL) activity.	Case study $N=$unspecified; monitored for several times for 1 week.	No	76% validity rate.	Google Scholar	Book chapter
[41]	Monekosso & Remagnino (2010); UK	Detection of (ADL) activity.	Case study $N=2$; monitored for several periods lasting 1 week.	No	Functionality system demonstrated.	Google Scholar	Journal
[42]	Munoz et al. (2012); Spain	Detection of (ADL) activity to identify significant events.	Case study $N=2$; monitoring period unknown.	No	Functionality system and guideline demonstrated.	Pubmed	Journal
[43]	Nazerfard et al. (2010); USA	Detection of (ADL) activity.	Case study $N=1$; 4 months of monitoring.	No	Functionality algorithm demonstrated to discover order of activities, usual start times and durations.	Google Scholar	Conference proceeding
[44]	Nazerfard et al. (2011); USA	Detection of (ADL) activity.	Case study $N=2$ married residents; 4 months of monitoring.	No	Functionality algorithm demonstrated to discover order of activities, usual start times and durations.	Google Scholar	Conference proceeding
[45]	Noury & Haddidi (2012); France	Detection of (ADL) activity.	Pilot study $N=5$; 1 monitored for 2 years (265 days of data), 1 resident monitored for 58 days and 2 residents monitored for 667 days, several subjects monitored for 502 days.	No	Feasibility use simulation data demonstrated; Markov model better results than Polya's model.	Pubmed	Journal
[46]	Popescu & Manot (2012); USA	Detecting (ADL) activity to identify changes in health status.	Mixed methods: Testing algorithm on retrospective dataset $N=6$; 2 months of monitoring data in 3 residents and 1–2 years in 3 other residents.	No	Simulated sensor data useful in developing algorithm development and testing; MIL used: AROC 0.7.	Pubmed	Journal
[47]	Poujaud et al. (2008); France	Detection of (ADL) activity.	Case study $N=1$; 1 year of monitoring.	No	Functionality demonstrated.	Pubmed	IEEE
[48]	Rahal et al. (2008); Canada	Detection of (ADL) activity and localization.	Simulating activities in laboratory setting $N=14$.	No	Accuracy 85%. System fast and robust.	Pubmed	Journal
[49]	Rantz et al. (2008); USA	Changes in health status, fall events.	Case study 2 out of $N=34$; retrospective analysis data.	No	Detection of health status possible with system, signals ignored by nurses.	Google Scholar	Journal
[50]	Rashidi & Cook (2010a); USA	Detection of (ADL) activity.	Case study $N=3$; 3 months of monitoring.	No	Functionality demonstrated: possible to recognize activities using no labeled data	Google Scholar	AAAI workshop

(continued)

Table 1. Continued

References	Author (year); country	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
					from target space, despite apartment layouts and residents schedules differed.		
[51]	Rashidi & Cook (2010b); USA	Detection of (ADL) activity.	Case study $N=2$; 3 months of monitoring.	No	Functionality demonstrated of COM model to discover activities and recognition by HMM of discovered activities.	Google Scholar	Conference proceeding
[52]	Rashidi et al. (2011); USA	Detection of (ADL) activity.	Testing activities in laboratory setting $N=20$.	No	ADM algorithm identified 80% predefined activities; 87.5% individual sensor events assigned to correct cluster; 73.8% original activities recognized by HMM (without clustering 48.6%) and 95.2% of ADM discovered activities. HMM accuracy original activities 61%.	Pubmed	Journal
[53]	Rowe et al. (2007); USA	Detection of night-time activity to prevent injuries and unattended exits.	Pilot study $N=53$; 12 months of monitoring. 26 received system.	Yes	Functionality system demonstrated. 20% controls potentially preventable fall event. Can reduce negative consequences night-time activity. Satisfied with system.	Google Scholar	Conference proceeding
[54]	Shin et al. (2011); Korea	Detection of (ADL) activity and atypical behaviour.	Pilot study $N=9$; 51 and 157 days with a mean of 101.56 days of monitoring.	No	Accuracy real data 90.5%.	Embase	Journal
[55]	Singla et al. (2008); USA	Detection of (ADL) activity.	Simulating activities in laboratory setting $N=22$.	No	Model overall accuracy 77.27% (test set), with individual accuracies ranging between 59.09% and 95.45% for four activities. MM 88.63% accuracy with temporal information.	Google Scholar	Conference workshop
[56]	Singla et al. (2009); USA	Detection of (ADL) activity.	Simulating activities in laboratory setting $N=20$.	No	Accuracy naïve Bayes classifier 66.08%; HMM 71.01% accuracy ($p<0.04$).	Pubmed	Journal
[57]	Singla et al. (2010); USA	Detection of (ADL) activity.	Simulating activities in laboratory setting $N=40$; 2 volunteers together present in smart apartment.	No	Accuracy model 73.15%; possible to distinguish between activities performed in smart home with multiple persons present.	Pubmed	Journal
[58]	Suzuki et al. (2006a); Japan	Detection of (ADL) activity and significant events.	Case study $N=1$; days and 6 months of monitoring.	No	Functionality system demonstrated.	Embase	Journal
[59]	Suzuki et al. (2006b); Japan	Detection of (ADL) activity and atypical behaviour.	Case study $N=3$; 28 days of monitoring.	No	Functionality system demonstrated.	Pubmed	Journal
[60]	Tapia et al. (2000); Mexico	Detection of (ADL) activity.	Case study $N=2$; 14 days of monitoring.	No		Google Scholar	Master thesis

[61]	Tomita et al. (2007); USA	Detection of (ADL) activity.	Randomized controlled trial with 46 receiving the system and 67 controls; 2 years of monitoring.	Yes	Detection accuracies ranging 25–89% depending on evaluation criteria used. 52–68% SH functions in use after 2 years. Reason non-use: unfriendly features 10× and unfamiliarity with system. 91% recommended use.	Cochrane	Journal
[62]	Virone (2008); USA	Detection of (ADL) activity and atypical behaviour.	Pilot study $N = 22$ in assisted living apartments; between 3 months and 1 year of monitoring; results two cases.	No	Functionality system demonstrated.	Pubmed	Journal
[63]	Virone (2009); USA	Detection of (ADL) activity and significant events.	Simulated case study $N = 3$ to test pattern recognition model.	No	Functionality system demonstrated.	Google Scholar	Journal
[64]	Wang et al. (2012); USA	Detection of (ADL) activity and changes in health status.	Case study $N = 3$; 1 month, 4 months and 3 months of monitoring respectively.	No	Dissimilarity results range 0.30–0.52: sensitive to catch lifestyle changes.	Pubmed	Journal
[65]	Willems et al. (2011); the Netherlands	Detection of (ADL) activity, significant events and changes in health status.	Implementation study $N = 116$; 2 years of monitoring.	No	Functionality system demonstrated.	Google Scholar	Conference publication
[66]	Wood et al. (2006); USA	Detection of (ADL) activity and changes in health status.	Case study $N = 3$; 25 days of monitoring in assisted living facility.	No	Functionality system demonstrated.	Google Scholar	IEEE journal
[67]	Zhang et al. (2010a); UK	Detection of (ADL) activity.	Description technology.	–	–	Google Scholar	Journal
[68]	Zhang et al. (2012); UK	Detection of (ADL) activity.	Testing algorithm on real data $N = 2$ for 4 weeks; on existing dataset.	No	Functionality algorithm demonstrated.	Pubmed	Journal

used to make distinctions between falls and ADL activities ($N = 3$), to detect changes in health status ($N = 1$), to detect gait velocity and walking periods ($N = 3$) and to detect transitions in postural state ($N = 6$).

Study characteristics

The use of body-worn sensor technology was described in one article. Validation of body-worn sensor technology was conducted by performing simulated falls or activities in a laboratory setting and/or by simulating activities in-home ($N = 20$). The number of pilot studies was small, with only three articles focusing on testing the use of body-worn sensors with several persons for periods ranging from 72 h to 9 months. Only one case study was performed. No longitudinal studies were conducted to study long-term effectiveness.

Outcomes

Research regarding the use of body-worn sensor technology focused mainly on demonstrating its functionality in terms of sensitivity and specificity (Table 2), which ranged from 62.5% to 100% and from 67.5% to 100%, respectively. Accuracy ranged from 59.09% to 95.45%. Determining the detection and/or error rate was described as the main outcome in five articles. In six articles, functionality was described in terms of more general outcomes. In the case study, reliability of using the system and the impressions of users were presented as outcomes.

Video monitoring

Eight articles described the use of video monitoring to detect activity and locate residents in their homes [95–102]. Cameras are placed on the ceiling and detect activity through silhouettes, background subtraction or ellipse tracking algorithms [95] (Table 3).

Aim of monitoring

Video monitoring technology was mainly used to detect (ADL) activities ($N = 6$), to recognise posture or postural transitions ($N = 4$) and to detect falls or other significant events ($N = 3$).

Study characteristics

The use of video monitoring technology was described in one article. Validation of video monitoring technology was conducted by performing simulated falls or activities in a laboratory setting and/or by simulating activities in-home ($N = 5$). Three articles validated video monitoring technology using existing datasets. One article described a case study in which two persons were monitored for 2 days. No pilot or longitudinal studies were conducted to study effectiveness.

Outcomes

Functionality of video monitoring was demonstrated in three articles, in terms of sensitivity, which ranged from 62.5% to 100%, and in terms of specificity, which ranged from 73% to 100%. Accuracy of monitoring ranged from 74.29% to 100% in three articles. In addition, false detection rates between 0.8 and 3% were demonstrated.

Pressure sensors

In total, three articles described the use of pressure sensor technology to detect the activity of individuals [103–105]. Pressure sensors are used to detect the presence of residents on chairs or in bed [104]. Pressure sensors were in all three studies used to detect sit-to-stand transfers and stand-to-sit transfers. In one article, the detection of (ADL) activity was also measured [104] (Table 4).

Study characteristics

Two studies validated the algorithms behind the use of pressure sensor technology in a laboratory setting ($N = 2$). One case study was conducted [105]. No pilot or longitudinal studies were conducted to study effectiveness.

Outcomes

Given that all articles focused on detecting transfers from sit-to-stand and from stand-to-sit, determining the length of transfer time was the main outcome in two articles. Determining maximum force on grab bars and range of contact with sensors were also outcomes in the article that measured transfer time. One article described functionality in terms of more general outcomes.

Sound recognition

Two articles described the use of sound recognition to detect the activity of individuals [106,107]. Sound recognition uses microphones to detect different classes of daily activity, e.g. the sound of doing the dishes or of the fall of an object or person [106].

Aim of monitoring

In both articles, the detection of (ADL) activities along with significant events like falls was the aim of monitoring (Table 5).

Study characteristics

Two studies validated the algorithms behind the use of sound recognition in a laboratory setting. No pilot or longitudinal studies were conducted to study effectiveness.

Outcomes

Determining the accuracy of sound recognition was in both articles the main outcome; accuracy ranged from 75.86% for the polynomial method to 92% for Gaussian Mixture Modelling.

Smart homes

In total, nine articles described the smart home concept [108–116]. Smart homes refer to any living or working environments that have been carefully constructed to assist people in carrying out required activities [117]. The home is fitted with devices, such as sensors, actuators and/or biomedical monitors, and it operates within a network. Data is transferred to a remote centre for collection and processing, as is the case with PIR motion sensors. Smart homes regulate, for instance, temperature, heating and lighting, without the interference of the residents (Table 6).

Aim of monitoring

Devices incorporated into smart homes aim to detect (ADL) activity and/or to generate alarms when significant events occur. Monitoring environmental conditions, significant events and changes in health status were also stated aims.

Study characteristics

The use of smart home technology was described in three articles. Two studies validated smart home technology in a laboratory setting by performing simulated activities, and one study validated the algorithm on an existing dataset by simulating activities. In addition, one article described a case study which consisted of a single person who was monitored for 28 days. One

Table 2. Body worn sensor technology.

References	Author (year)	Aim of monitoring	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[69]	Barralon et al. (2005); France	Postural transitions; walk detection.	Simulating activities in elderly home $N = 1$; elderly subjects.	No	Identification different activities (walking, postural transitions, time in each posture) possible.	Pubmed	Conference proceeding
[70]	Barralon et al. (2006); France	Walk detection.	Simulating activities in elderly home $N = 20$; elderly subjects	No	Sens. 78.5%; Spec. 67.6%.	Pubmed	Conference proceeding
[71]	Bloch et al. (2011); France	Detection of significant events.	Pilot study $N = 10$ in geriatric ward; 9 months of monitoring.	No	Sens. 62.5%; Spec. 99.5%.	Pubmed	Journal
[72]	Boissy et al. (2007); Canada	Detection of significant events.	Simulating falls in laboratory setting $N = 10$.	No	Sens. 93%; false-positive rate 29%; Spec. 71%.	Pubmed	Journal
[73]	Bourke & Lyons (2008a); Ireland	Differentiating between (ADL) activities and significant events.	(1) Simulating falls in laboratory setting $N = 10$ young volunteers; (2) simulating ADL activities in laboratory setting $N = 10$.	No	Falls can be distinguished from ADL with 100% accuracy.	Pubmed	Journal
[74]	Bourke et al. (2008b); Ireland	Detection of ADL activity and significant events.	Simulating falls in laboratory setting $N = 5$ healthy individuals.	No	Falls can be distinguished from normal ADL with 100% accuracy; 0.941: Coefficient of Multiple Correlations; low mean percentage error (6.74%) between signals from inertial sensor to those from optical motion capture system.	Embase	Journal
[75]	Bourke et al. (2008c); Ireland	Detection of significant events.	Simulating ADL activities and falls in laboratory setting $N = 11$.	No	Sens. > 90%; Spec. > 99%	Pubmed	Conference proceeding
[76]	Bourke et al. (2008d); Ireland	Detection of ADL activities and significant events.	Pilot study $N = 10$; 4 weeks of monitoring.	No	Fall sensor: 115 fall events, 73 fall recovery messages, 42 fall alerts; care centre received: 532 fall events; 199 fall recovery and 9 fall-alerts.	Pubmed	Conference proceeding
[77]	Chao et al. (2009); China	Detection of (ADL) activities, significant events and postural transitions.	Simulating falls, postural transitions, and activities in laboratory setting $N = 7$.	No	Strategy AC TH: larger area under ROC curves, larger sensitivity and specificity than AM TH.	Pubmed	Journal
[78]	Diermaier et al. (2010); Austria	Detection of (ADL) activities.	Case study $N = 1$.	No	Positive impression use; reliability sensors disappointing.	Google Scholar	Book chapter
[79]	Doherty & Oh (2012); Canada	Detection (ADL) activities, health status.	Pilot study $N = 40$ diabetic patients monitored for 72 h.	No	Activity detection algorithms successful in identifying activities.	Embase	Journal
[80]	Godfrey et al. (2011); UK	Detection of (ADL) activities and postural transitions.	Simulating activities in laboratory setting $N = 10$ healthy	Yes	Sensitivity and specificity of 86–92% young healthy	Pubmed	Journal

(continued)

Table 2. Continued

References	Author (year)	Aim of monitoring	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
			individuals; simulating activities in laboratory setting $N = 10$ healthy elderly persons.		subjects in a controlled setting; 83–89% elderly healthy subjects in a home environment.		
[81]	Hansen et al. (2005); Denmark	Detection of significant events.	Simulating activities $N = 2$ elderly persons in own home.	No	Functionality system demonstrated.	Google Scholar	Journal
[82]	He et al. (2007); USA	Detection of (ADL) activity.	Simulating 11 activity scenarios in laboratory setting $N = 5$.	No	Activity detection rate 95.2%.	Pubmed	Conference proceeding
[83]	Kang et al. (2010); Korea	Detection of (ADL) activity.	Simulating activities in laboratory setting $N = 5$; $N = 1$ monitored during 3-h experiment	No	Activity detection rate 96%; 98% movements successfully classified.	Cinahl	Journal
[84]	Kangas et al. (2007); Finland	Detection of significant events.	Simulating activities in laboratory setting $N = 2$	No	Waist and head sensors: sensitivity and specificity 100%; wrist low sensitivity and specificity.	Pubmed	Conference proceeding
[85]	Kangas et al. (2009); Finland	Differentiating between ADL activities and fall events.	Simulating falls in laboratory setting $N = 20$ aged 40–65 and $N = 21$ aged 58–98 years old.	Yes	Sens. 97.5%; Spec. 100%.	Embase	Journal
[86]	Lee et al. (2007); Korea	Detection of (ADL) activity, significant events, postural transition.	Simulating activities, postures and falls in laboratory setting $N = 30$.	No	Fall detection rate 93.2%.	Pubmed	Conference proceeding
[87]	Lee & Lee (2008); Korea	Detection of (ADL) activity, significant events, postural transition.	Simulating activities, postures and falls in laboratory setting $N = 30$.	No	Fall detection rate 93.6%.	Embase	Journal
[88]	Lindemann et al. (2005); Germany	Differentiating between significant events and (ADL) activity.	Simulating falls in laboratory setting $N = 1$; 1 day of monitoring $N = 1$.	No	Functionality demonstrated: high sensitivity and high specificity.	Pubmed	Journal
[89]	Najafi et al. (2003); Switzerland	Detection of postural transitions and walking periods.	(1) Simulating gait in laboratory setting $N = 11$; (2) monitoring postural transitions in hospital $N = 24$; (3) monitoring 45–60 min physical activity $N = 9$.	No	(1) Overall Sen.: 99% different PTs; Sens. 93%, Spec. 82% sit-to-stand; 82% and 94% stand-to-sit. Accuracy study 1 and 2 >99% identifying transfers and posture changes. (3) Sens. >90% classification physical activities; Sens. 90.2%, Spec.: 93.4% sitting; 92.2% and 92.1% ‘‘standing + walking"; 98.4% and 99.7% lying. Overall detection errors 3.9% ‘‘standing + walking"; 4.1% sitting, 0.3% lying. Overall symm. mean av. errors 12% for	Pubmed	Journal

					''standing + walking''; 8.2% sitting, 1.3% lying.		
[90]	Naranjo-Hernandez et al. (2012a); Spain	Detection (ADL) activity.	Simulating activities in laboratory setting $N = 6$.	No	Feasibility demonstrated of prototype and proposed classification and estimation algorithms.	Pubmed	Journal
[91]	Naranjo-Hernandez et al. (2012b); Spain	Detection (ADL) activity.	Simulating activities in laboratory setting $N = 6$.	No	100% impact detection; fall detection 100% sensitivity and 95.68% specificity; 100% ADL level classification.	Pubmed	Journal
[92]	Stroiescu et al. (2011); Ireland	Detection of significant events.	Description technology	–	–	Pubmed	Conference Proceeding
[93]	Wu & Xue (2008); USA	Detection of significant events.	Simulated activities and falls in laboratory setting $N = 10$ young and $N = 14$ elderly subjects.	Yes	Functionality demonstrated: separating falls from non falls, detecting falls before landing (at least 70 ms before impact)	Pubmed	Journal
[94]	Zhang et al. (2010b); UK	Detection of (ADL) activity.	Simulating activities in laboratory setting $N = 10$.	No	82.8% accuracy.	Google Scholar	Conference proceeding

article described a pilot study in which nine persons were monitored for 6 months. No studies were conducted to study long-term effectiveness.

Outcomes

Functionality was demonstrated in terms of accuracy in four out of nine articles; it ranged from 75.86% to 95.7%. One article also described the functionality of smart home technology in more general terms. The pilot study focused on qualitative outcomes of using smart home technology; the overall perception was positive.

Multicomponent monitoring technologies

In total, 31 articles described the use of more than one monitoring technology [5,118–147], e.g. combining an accelerometer with cameras and/or PIR motion sensors. Combinations of the five main types of monitoring technology were the most frequent; these were very diverse in nature (Table 7).

Most frequently encountered was the combination of PIR motion sensor technology and video monitoring ($N = 6$). Next most frequent was a combination of body-worn sensors and PIR motion sensor technology ($N = 5$), and then pressure sensor technology combined with PIR motion sensors ($N = 4$). PIR motion sensor technology was present in nine different types of combinations.

Aim of monitoring

Twenty-three monitoring technology combinations described detection of (ADL) activity as the aim of monitoring. Detection of significant events was monitored by 13 combinations.

Study characteristics

A description of multicomponent technologies was given by itself in three articles. Most articles described validation studies that had taken place within a laboratory setting ($N = 18$). One algorithm was validated by testing on a real dataset. In addition, 10 pilot studies were performed, with durations ranging from 3 weeks to 3 years. No studies were conducted to study long-term effectiveness.

Outcomes

Functionality was demonstrated in terms of accuracy in 10 articles, ranging from 50% to 100%. Sensitivity and specificity were used in six articles to demonstrate functionality, sensitivity ranging from 62% to 100% and specificity ranging from 75% to 96.7%. In four articles, accuracy, sensitivity and specificity measures were all used. In addition, five articles described functionality of the identified multicomponent monitoring technology in more general terms. Quality of life increased within different target groups that were using the same studied monitoring technology ($N = 4$), e.g. residents and professional caregivers or residents and informal caregivers [119,120]. Acceptance was high; the use of multicomponent monitoring technology increased a sense of safety and helped to postpone institutionalisation. An increase in quality of life was demonstrated for both residents and professional and informal caregivers. However, this increase was not significant; a significant increase in hours of informal care provided was also seen. Three articles focused on cost measures; they described a decrease in billable care interventions and in costs of health care, and an increase in care efficiency and postponement of institutionalisation.

Table 3. Summary of video monitoring technology.

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[95]	Aertssen et al. (2011); the Netherlands.	Postural transitions: walking, bending, sitting with fish eye camera.	Simulating of activities in laboratory setting $N = 4$; case study $N = 4$ monitored for 1 single day.	No	Simulations: 93% accuracy; real data: 80–100% accuracy.	Google Scholar	Master thesis
[96]	Brulin et al. (2012); France	Posture recognition based on human silhouette.	Testing algorithm on existing dataset.	No	74.29% accuracy.	Pubmed	Journal
[97]	Leone et al. (2011); Italy	Detection of significant events, ADL activity with 3D range camera.	Testing simulating falls and ADL activities on existing dataset.	No	Sens. 100%; Spec. 100% using 3 thresholds in conjunction.	Pubmed	Journal
[98]	Nait-Charif & McKenna (2004); UK	Detection of (ADL) activity with coarse ellipse model.	Case study $N = 1$; 2 days of monitoring.	No	Functionality demonstrated; 3% tracking error.	Google Scholar	Conference proceeding
[99]	Sacco et al. (2012); France	Detection of (ADL) activity with monocular video cameras.	Scenario testing in laboratory setting $N = 64$; two protocols.	Yes	(1) Sens. 94%; Spec. 100%; (2): Sens. 89%; Spec. 73%.	Pubmed	Journal
[100]	Seki (2009); Japan	Detection of (ADL) activity with omni-directional vision sensor.	Simulating activities in laboratory setting $N = 1$	No	Effectiveness algorithm demonstrated.	Embase	Conference proceeding
[101]	Varcheie et al. (2010); Canada	Detection of (ADL) activity, significant events, and posture with background subtraction.	Testing algorithm on existing dataset.	No	Outperforms classic GMM background subtraction method: less false positive detection for similar true positive results.	Pubmed	Journal
[102]	Yu et al. (2012); UK	Detection of falls, postures and activities with background subtraction.	Simulating postures, activities and falls in laboratory setting $N = 15$.	No	97.08% fall detection rate; 0.8% false fall detection rate.	Pubmed	Journal

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Table 4. Summary of pressure sensor technology.

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[103]	Arcelus et al. (2009a); Canada	Detection of ADL activity; sit-to-stand transfers and stand-to-sit transfers with bed and floor sensors.	Testing SiSt- transfers young adults ($N=10$) versus older adults ($N=5$) versus post-stroke ($N=5$) versus post-hip fracture ($N=5$) in laboratory setting.	Yes	Young SiSt ± 2.31 and older adults SiSt 2.88 s. Post-hip fracture SiSt ± 3.32 and post-stroke SiSt ± 5.00 s.	Pubmed	Journal
[104]	Arcelus et al. (2009b); Canada	Detection of sit-to-stand transfers and stand-to-sit transfers with commode grab bar pressure sensors.	Laboratory testing young ($N=10$) versus older adults ($N=11$).	Yes	StSi and SiSt sequences characterized by transfer length, maximum force and range of contact location. Older adults longer StSi and SiSt times and less force.	Pubmed	Conference
[105]	Arcelus et al. (2010); Canada	Detection of sit-to-stand transfers and stand-to-sit transfers with bed and commode grab bar pressure sensors.	Case study $N=2$; results of 1 day	No	Functionality demonstrated to keep track of potential warning signs.	Google Scholar	Conference

Table 5. Summary of sound recognition technology.

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[106]	Fleury et al. (2008); France	Detection of (ADL) activity and significant events.	Simulating activities in laboratory setting $N=-13$.	No	Gaussian Kernel 86.21% accuracy; Polynomial method 75.86% accuracy.	Pubmed	Conference proceeding
[107]	Vacher et al. (2011); France	Detection of (ADL) activities and significant events.	Laboratory testing performing daily activities $N=21$.	No	GMM 92% accuracy; SVM 87% accuracy.	Pubmed	Conference proceeding

Table 6. Summary of smart home technology.

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article
[108]	Alam et al. (2011); Malaysia.	Detection of (ADL) activity and environmental conditions.	Testing algorithm on existing dataset MavHome inhabitants $N = 50$; monitored for 1 month.	No	88.1% prediction accuracy.	PsycINFO	Journal
[109]	Augusto et al. (2008); UK	Detection of (ADL) activity.	Description technology.	–	–	Google Scholar	Journal
[110]	Brinkmann et al. (2008); Germany	Detection of (ADL) activity and significant events.	Description technology.	–	–	Google Scholar	Conference proceeding
[111]	Demiris et al. (2008); USA	Detection of (ADL) activity.	Pilot study $N = 9$ in-home monitoring for 6 months.	No	75 interviews, 3 observational sessions; overall positive perception sensor technology; no interference daily activity or privacy concerns.	Pubmed	Journal
[112]	Fernandez-Luque et al. (2010); Spain	Detection of significant events and changes in health status.	Description technology.	–	–	Pubmed	Conference proceeding
[113]	Fleury et al. (2009); France	Detection of (ADL) activity.	Simulating activities in Health Smart Home $N = 13$ young healthy subjects; testing algorithm on real dataset.	No	GMM: 86.21% accuracy; Polynomial method: 75.86% accuracy.	Pubmed	Conference proceeding
[114]	Fleury et al. (2010); France	Detection of (ADL) activity.	Simulating activities $N = 13$ young healthy subjects; testing algorithm on real dataset.	No	GMM: 86.21% accuracy; Polynomial method: 75.86% accuracy.	Pubmed	Journal
[115]	Hong & Nugent (2011); UK	Detection of (ADL) activity.	Case study $N = 1$; in-home monitoring 28 days.	No	Overall class accuracy of 83.4% and time slice accuracy of 95.7%. Class accuracies increased.	Pubmed	Journal
[116]	Jakkula & Cook (2008); USA	Detection of (ADL) activity and significant events.	Testing algorithm on existing dataset of 59 days.	No	No false positives in synthetic dataset and all expected anomalies detected; no anomalies in real data reported. No false anomalies reported.	Pubmed	Journal

Table 7. Summary of multicomponent technology.

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article	Type of technology
[118]	Aghajan et al. (2007); USA	Detection of significant events.	Description technology.	–	–	Google Scholar	Journal	Accelerometer, PIR motion sensors, camera
[5]	Alwan et al. (2006a); USA	Detection ADL activities, changes in health status and key alert conditions.	Pilot study $N = 22$; 3 months of monitoring.	No	High acceptance; increase quality of life for some (SWLS; $p = 0.0977$; Sign reduction variance SWLS ($p = 0.0384$); Useful in care coordination, care planning, detecting health status change.	Google Scholar	Journal	PIR motion sensors, stove sensor, bed pressure sensor
[119]	Alwan et al. (2006b); USA	Detection ADL activities and key alert conditions.	Pilot study $N = 15$ residents and $N = 7$ caregivers; 3 months of monitoring.	No	Significant increase quality of life (SWLS; $p = 0.031$) in residents; no sign. changes CSI ($p = 0.771$) or CBI (0.386) in professional caregivers.	Google Scholar	Conference proceeding	PIR motion sensors, stove sensor, bed pressure sensor
[120]	Alwan et al. (2006c); USA	Detection ADL activities and key alert conditions.	Pilot study $N = 25$ seniors and $N = 26$ informal caregivers; 4 months of monitoring.	No	No sign. increase quality of life residents (SWLS; $p = 0.2822$) or informal carers (SWLS; $p = 0.5081$); no significant changes in CSI ($p = 0.3336$) or CBI ($p = 0.8674$) informal caregivers; significant increase in hours informal care provided by carers ($p = 0.0401$).	Google Scholar	Journal	PIR motion sensors, stove sensor, pressure sensors
[121]	Alwan et al. (2007); USA	Detection ADL activities and key alert conditions, physiological parameters.	Case-matched controlled pilot study; $N = 42$ (21/21) residents and $N = 12$ caregivers; 3 months of monitoring in assisted living facility.	Yes	Differences between cohorts: reductions in billable interventions (47 versus 73, $p = 0.040$), hospital days (7 versus 33, $p = 0.004$), estimated cost of care (\$21 187.02 versus \$67 753.88, monitoring cost included, $p = 0.034$). Positive impact caregivers' efficiency.	Google Scholar	Journal	PIR motion sensors, stove sensor, pressure sensors

(continued)

Table 7. Continued

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article	Type of technology
[122]	Ariani et al. (2012); Australia	Detection of significant events.	Algorithm testing on scenarios in existing dataset.	No	Sens.:100%, Spec.: 77.14%, Accuracy: 89.33%.	Embase	Journal	Ambient sensors, PIR motion sensors, pressure mats
[123]	Bang et al. (2008); Korea	Detection of ADL activities.	Experiment in laboratory testing $N=6$.	No	Overall recognition rate over 97% over 8 component ADLs.	Pubmed	Conference proceeding	Accelerometer and environmental PIR sensors
[124]	Bianchi et al. (2009); Italy	Detection of significant events.	Laboratory-based simulated falls $N=15$.	No	Algorithm including pressure information: Sens. 97.8%; Spec 96.7%.	Pubmed	Conference proceeding	Accelerometer and barometric pressure sensors
[125]	Bianchi et al. (2010); Italy	Detection of (ADL) activity and significant events	Laboratory-based simulated falls $N=20$	No	Accuracy 96.9%, Sens. 97.5%, Spec. 96.5%; accelerometer alone: Accuracy 85.3%, Sens. 75%, Spec 91.5%.	Pubmed	Journal	Accelerometer and barometric pressure sensors
[126]	Biswas et al. (2010); Singapore	Detection of (ADL) activities; localization.	Description technology.	–	–	Google Scholar	Journal	Wearable sensors and ambient sensors
[127]	Cao et al. (2009); China	Detection of (ADL) activity, significant events and localization.	Simulated falls in laboratory setting, activities according to four scenarios.	No	Proposed model effective.	Google Scholar	Conference proceeding	Multimodal sensors, video monitoring, accelerometer
[128]	Lymberopoulos & Savvides (2008); USA	Detection of (ADL) activity.	Case study $N=1$; monitored for 30 days in test bed.	No	Functionality methodology demonstrated.	Google Scholar	Conference proceeding	Video monitoring, PIR motion sensors, door sensors
[129]	Della Toffola et al. (2011); Switzerland	Detection of (ADL) activity and significant events.	Laboratory testing of system $N=$ unknown.	No	Functionality demonstrated.	Embase	Conference proceeding	Accelerometers, home robot, ambient sensors
[130]	Guettari et al. (2010); France	Localization.	Description technology.	–	–	Pubmed	Conference proceeding	PIR motion sensors and sound recognition
[131]	Hein et al. (2010); Germany	Detection of (ADL) activities.	Simulating activities in laboratory setting $N=6$ aged 25–40 years old and $N=5$ 72–84 years old.	Yes	Recognition rate ''preparation + intake food or beverages'' Food preparation: Sens. 74.7%, Spec. 84.2%. ''Upright'' activities: Sens. 91.8%, Spec. 95.8%; ''Sedentary'': Sens. 96.1%, Spec. 90.3%.	Google Scholar	Journal	Accelerometer, video monitoring, PIR motion sensors, door sensors
[132]	Hou et al. (2007); USA	Detection (ADL) activities, significant events and changes in health status.	Pilot study $N=12$ (2 cases/10 controls); 3 weeks of monitoring.	Yes	Functionality system demonstrated. 100% adherence. Technical directions to recognized to improve system.	Google Scholar	Conference proceeding	Combination of RFID technologies

[133]	Kinney et al. (2004); USA	Detection of (ADL) activities.	Pilot study $N=19$ families; 6 months of monitoring	No	Advantages > disadvantages; easier to keep track, annoyed by alerts; cost technology \$400 to equip home, \$90 per month maintenance.	Google Scholar	Journal	Video monitoring, PIR motion sensors
[134]	Medjahed et al. (2009); France	Detection of (ADL) activities.	Simulating activities in laboratory setting $N=14$	No	97% good ADL detection.	Google Scholar	Conference proceeding	Sound recognition, PIR motion sensors, physiological sensors, state-change sensors
[135]	Merilahti et al. (2007); Finland	Detection of sleep patterns.	Pilot study $N=17$; 3 months.	Yes	Correlation visually analysed total sleep time and actigraphy $(r)=0.662$, $p<0.01$; Comparison subjective and objective sleep quality significant correlation: $r=0.270$, $p<0.01$.	Pubmed	Conference proceeding	Actigraphy, ambient sensors
[136]	Nyan et al. (2006); Singapore	Detection of (ADL) activities, significant.	Simulating falls in laboratory setting $N=10$.	No	Waist: Sens. 100%, Spec.92.5%, Negative predictive value 100%, Positive predictive value 80%; Sternum: 100%, 94%, 100%, 83.3% respectively. Underarm: 100%, 97.5%, 100%, 92.3% respectively.	Pubmed	Journal	Gyroscopes, video monitoring
[137]	Riikonen et al. (2010); Finland	Detection of significant events.	Pilot $N=25$; 3 years of monitoring.	No	Cost devices installed €30–2100, €600 on average. Postponement institutionalization 8 months on average.	Google Scholar	Journal	Testing of 29 different technologies
[138]	Roy et al. (2011); Canada	Detection of (ADL) activities.	Testing algorithm on existing dataset, three filters.	No	(1) Recognition erroneous behaviours 56.7%; Behaviour (overall 62.5%). (2) 63.3% erroneous behaviour (overall 67.5%). (3) 100% recognition erroneous behaviour (overall 95%).	PsycINFO	Journal	Pressure sensors, accelerometer, video monitoring, PIR motion sensors
[139]	Sim et al. (2011); Singapore	Detection of (ADL) activities.	Simulating data in smart home test bed $N=1$.	No	Accuracy system correlated patterns 35.5% higher than system using frequent patterns.	Pubmed	Conference proceeding	RFID, accelerometer, reed switches, PIR motion sensors, pressure sensors

(continued)

Table 7. Continued

References	Author (year)	Aim	Study characteristics	Comparator group?	Main outcomes	Database	Type of article	Type of technology
[140]	Srinivasan et al. (2007); USA	Detection of significant events, posture, walking.	Simulating falls in laboratory setting $N=15$	No	Without motion:detection rate 91/96, false alarm rate 11/1288; With motion: detection rate 9/96, false alarm rate 0/1288.	Pubmed	Conference proceeding	Accelerometer, PIR motion sensors
[141]	Tolkiehn et al. (2011); UK	Detection of significant events, and ADL activity.	Simulating falls in laboratory setting $N=12$.	No	Accelerometer: accuracy 81.48%, Sens. 79.08%, Spec. 83.33%. Barometric sensor + accelerometer, fall accuracy 89.97%, Sens. 87.77%, Spec. 85.24%. prediction of fall direction: 94.12% accuracy.	Pubmed	Conference proceeding	Accelerometer, barometric pressure sensor
[142]	Van Hoof et al. (2011); the Netherlands	Detection of (ADL) activities, fire, wandering.	Pilot study $N=18$; 8–23 months of monitoring.	No	Use of system increased sense of safety and security, helped to postpone institutionalization.	Embase	Journal	PIR motion sensors, video monitoring
[143]	Villacorate et al. (2011);Spain	Detection of (ADL) activity, significant events.	Simulating activity scenarios in laboratory setting $N=2$.	No	Functionality demonstrated.	Pubmed	Journal	Video monitoring, sound recognition
[144]	Zhou et al. (2008); Singapore	Detection of (ADL) activity.	Simulating activities in test bed $N=4$, 1 month of monitoring.	No	Overall ''precision'' of correct classification 92%; ''recall'': correctly inferring a true activity 92%.	Google Scholar	Conference proceeding	Video monitoring, RFID wristband
[145]	Zhou et al. (2011); Singapore	Detection of (ADL) activity.	Simulating activities in test bed $N=4$; 1 month of monitoring.	No	Overall ''precision'' of correct classification 92%; ''recall'': correctly inferring a true activity 92%.	Google Scholar	Journal	Video monitoring, PIR motion sensors
[146]	Zouba et al. (2009a); France	Detection of (ADL) activity.	Simulating activities in laboratory setting $N=2$.	No	Precision recognizing postures and events ranged 62–94%; Sens. 62–87%.	Google Scholar	Journal	Video monitoring, PIR motion sensors
[147]	Zouba et al. (2009b); France	Detection of (ADL) activity.	Simulating activities in laboratory setting $N=14$.	No	Precision range 50–80%; Sens. Range 66–100%.	Google Scholar	Conference proceeding	Video monitoring, PIR motion sensors

Aluminium foil

One article described the use of aluminium foil as the sensor of static electricity and electromagnetic energy with the aim of detecting motion or activity of a person in the living environment [148]. An initial pilot test was performed in a laboratory setting and the data showed true positive rates of 98% and a high detection rate with false positives and low false negative rates of 2% [148].

Discussion

The aim of this review was to investigate what kind of monitoring technologies exist to monitor activity in-home and what is known in the literature about the effects of these technologies. A large number of studies were found, ranging from descriptions of technologies to four articles describing longitudinal studies that were conducted to demonstrate the technologies' effectiveness. Most research was conducted within the area of PIR motion sensor technology, followed by body-worn sensors. Whilst the extent of research into the use of monitoring technologies is great, most articles only focused on demonstrating that the functionality of the proposed monitoring technology by simulating activities in a laboratory setting or on an existing dataset. As a result, the functionality of most systems has only been demonstrated in general terms or in terms of accuracy, sensitivity and specificity. The long-term effects of using monitoring technology are less well studied. For instance, 25 out of 141 articles described pilot studies, with 11 focusing on the use of PIR motion sensor technology and 10 on the use of multicomponent monitoring technology; study durations ranged from 3 weeks to 3 years. Only four articles described longitudinal studies, including one randomised controlled trial and one implementation study. All of these studies focused on the use of PIR motion sensor technology.

The results of the pilot studies and the longitudinal studies suggest positive effects of using monitoring technology on residents, professional caregivers and informal caregivers. These findings are, however, not conclusive. Acceptance and usability of the systems were generally perceived as high by end users. The available studies show promising results, indicating positive effects on care efficiency, postponed institutionalisation and lowered care costs. However, not everyone was positive; concerns about privacy were presented, and a significant increase in hours of informal care provided was described. It is surprising that in a field where so many developments are taking place, only this little research is being done into the effects of these technologies in care practice.

It is not very likely that we have missed many relevant studies. The document search was guided by a comprehensive list of key terms. Scientific databases were extensively searched for articles; this was complemented by a search using Google Scholar for conference publications and grey literature. However, relevant articles may have been overlooked due to not being clearly identifiable in titles or abstracts as per our inclusion and exclusion criteria. It is also possible that articles were overlooked due to the choice of our key terms.

Based on this review, it is not possible to conclude which technology is most promising. The results suggest that a combination of technologies is probably the most effective solution, but it is unclear which combination that should be, since very different combinations have been described. The use of PIR sensors is very attractive. They are technically relatively simple and robust, and not very expensive. This probably explains why PIR sensors gain much attention in research. The main challenge regarding effective use is to develop algorithms that enable the detection of clinically relevant changes and situations without too many false alarms. Such algorithms can only be developed when the technology is used for a substantial period of time and with substantial numbers of users. This type of research is lacking.

This review demonstrates that the use of monitoring technology for the detection of (ADL) activities, significant events like falls and changes in health status, is a promising field of applications for care situations. However, research within this field is still in its infancy. It is therefore recommended that this research is taken to the next level, which would include studying the usability, functionality and effects of these technologies in real-life settings, and the development of ''intelligent'' algorithms for the analysis and interpretation of the data collected by these systems.

Declaration of interest

The authors report no declarations of interest.

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