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Review Article

Advances in Sensor Monitoring Effectiveness and Applicability: A Systematic Review and Update

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Abstract

Background and Objectives: To provide an updated review article studying the applicability and effectiveness of sensor networks in measuring and supporting activities of daily living (ADLs) among non-demented older adults.

Research Design and Methods: Systematic review following PRISMA guidelines. Systematic search of PubMed, Embase, PsycINFO, INSPEC, and the Cochrane Library, from October 26, 2012 to January 3, 2018 for empirical studies, measuring and supporting ADLs among independently living, non-demented older adults, investigating wireless sensor monitoring networks.

Results: The search queries yielded 10,782 hits of which 162 articles were manually reviewed. Following exclusion criteria, 13 relevant articles were retained. Although various types of sensor networks with different analyzing algorithms were proposed, from simple video monitoring to complex sensor networks distributed throughout a house, all articles supported the use of wireless sensors for identifying changes in activity patterns.

Discussion and Implications: Wireless sensor networks appear to be developing into an effective solution for measuring ADLs and for identifying changes in their patterns. They offer a promising solution to support older adults living independently at home. However, there is too much focus on technology, and practical usefulness still needs to be further elaborated. Sensors should focus on ADLs that are sensitive to the earliest signs of cognitive decline, as well as quantitative markers, such as errors in the execution of ADLs.

Keywords: Activities of daily living, Surveillance, Support, Independent living, Wireless sensors

Technology develops at exponential rates. It is reasonable to assume that since Pol and colleagues published their 2013 systematic review, there have been many such advances in the field of sensor monitoring to measure and support daily functioning for independently living older adults (65 years and older) (Pol et al., 2013). Such advances can be used to help with *aging in place*, the ability to live in one's own home and community safely, independently, and comfortably, regardless of age, income, or ability level (Centers for Disease Control and Prevention – National Center for Environmental Health, 2017). This is important because the vast majority of older adults desire to remain at home despite multiple comorbidities, and this population is projected to increase (WHO, 2011).

Activities of daily living (ADLs) can be divided into basic (bADL) and instrumental (iADL). Successful aging in place relies on the ability to pursue them both (Lawton, 1990). bADLs involve *bathing*, *dressing*, *toileting*, *transfer*, *continence*, and *feeding* (Katz, Ford, Moskowitz, Jackson, & Jaffe, 1963). IADLs involve more complicated tasks such as *using the telephone*, *traveling*, *shopping*, *preparing meals*, *doing housework*, *managing medications*, and *handling money* (Lawton & Brody, 1969). As age advances, functional capabilities decline due to physical limitations and cognitive decline, reducing the ability to perform ADLs (Covinsky et al., 2003; Mioshi et al., 2007; Seidel et al., 2009). Mild cognitive impairment (MCI) describes the first steps of cognitive decline, which would eventually result in an inability to perform iADLs, then bADLs, and consequently, the failure of successful aging in place. Therefore, surveillance of these abilities is a useful tool in tracking the functional status and successful aging in place (Cornelis, Gorus, Beyer, Bautmans, & de Vriendt, 2017; Covinsky et al., 2003; Pol et al., 2013).

Using sensor technology to measure ADLs offers a more objective alternative than assessment through questionnaires or direct observation. Since manifestations of cognitive deficits fluctuate, sensor technology avoids the risk of bias from serial measurements across a few time points by providing continuous monitoring (Cornelis et al., 2017; Pol et al., 2013). Sensors can be wearable or non-wearable (environment attached). Wearable sensors are attached to the subject and allow pervasive monitoring of physiological and accelometric signals during ADLs and allow for identification and tracking (Debes et al., 2016). When multiple sensors are incorporated, a *network* is formed. Non-wearable sensor networks consist of multiple simple binary devices measuring movement within the in-home environment. These may include infrared motion detectors, flush sensors, or contact sensors on doors (Pol et al., 2013). Sensor data from these *sensor networks* are wirelessly transmitted to track ADLs, analyzed, and could potentially offer possibilities for *remote home monitoring*.

Wearable sensor network technology has been well investigated (D'Onofrioa et al., 2017; Lowe & Ólaighin, 2014; Peetoom, Lexis, Joore, Dirksen, & De Witte, 2015; Yusif, Soar, & Hafeez-Baig, 2016). In addition, many validation studies exist for new sensor networks that focus on establishing the algorithms used in developing the system (Ji, Yang, & Yu, 2013; Nguyen, Nebel, & Florez-Revuelta, 2016; Ryoo, 2011). However, to our knowledge, no systematic review has been conducted since the 2013 article by Pol and colleagues that investigates the application and effectiveness of sensor monitoring for the evolution of cognitive function (Peetoom, Lexis, Joore, Dirksen, & de Witte, 2015). Since Pol and colleagues concluded 6 years ago that there are gaps in technological development, its application, and effectiveness in daily practice, and the evidence of sensor network effectiveness is lacking, the need to update their article is apparent (Pol et al., 2013).

This systematic review aims to update the review conducted in 2013 by Pol and colleagues with the latest peer-reviewed empirical studies available, following the original article's aim "to study the application and effectiveness of sensor monitoring to measure and eventually support daily functioning in older people living independently at home." Considering the inclination of rapid progress in technology, this review will clarify if the gap has narrowed between the application and effectiveness of passive sensor monitoring to measure and support daily functioning, and if the evidence of efficacy can be clarified.

Methods

Data Sources

A systematic review following the PRISMA guidelines was conducted of the electronic databases, including PubMed, Embase, PsycINFO, INSPECT, and the Cochrane Library, using the original search queries listed in the research protocols from Pol and colleagues (2013). Each database had its own customized search query. These search queries were duplicated and adjusted for the date, from the last search date of the Pol and colleagues' article (March 10, 2012) to the last search date of this current article (January 3, 2018). See the Supplementary Data for the search criteria, updated for the current search period. Searches were conducted between December 18, 2017 and January 3, 2018 by the first author (EL).

Study Selection

One reviewer (EL) screened titles and abstracts for inclusion that resulted from the database search hits using the original search queries, adapted for dates. Two reviewers (EL, LN) then screened the full texts of the retained articles. Differences were resolved by a third reviewer (SK). Selection criteria were retained from the previous study and their application is illustrated in Figure 1.

Inclusion criteria:

1. Empirical studies that described the use of wireless sensor monitoring to measure daily functioning or to support older adults with daily functioning
2. Study subjects included older adults, aged 65 years and older, living independently
3. Daily functioning was a primary outcome measured in the study

Exclusion criteria are listed in Figure 1.

Data Extraction and Quality Assessment

Data points were extracted from the included articles and summarized in Tables 1 and 2. These tables were reproduced from the original Pol and colleague's article to ensure congruency and to allow the original tables to be updated with new data. Of special note, in Table 2, we defined *clinical practice* as sensor systems that are intended for permanent installation, or installed for the study, and remain after its completion. We define *possibilities for clinical practice* as having the potential to be permanently installed, as suggested in the articles. We define *professional*

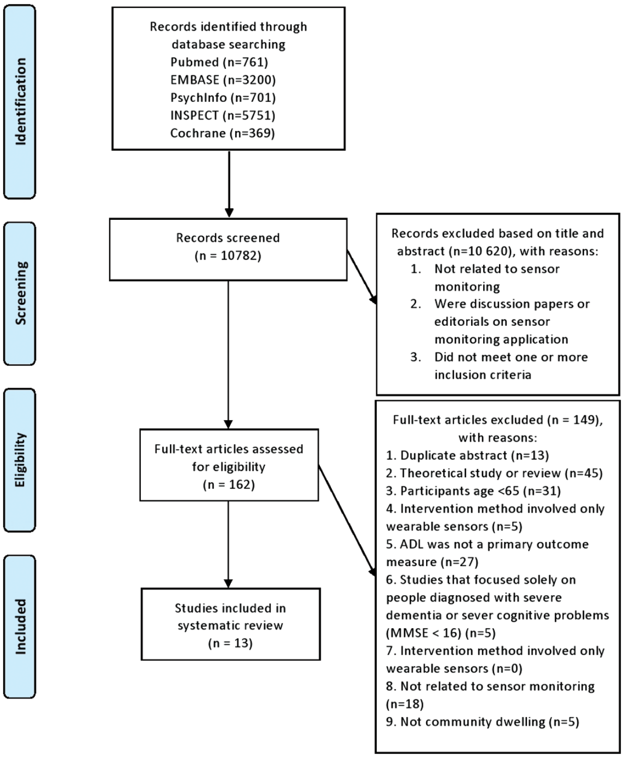

Figure 1. Illustration of article selection process (Moher et al.; PRISMA Group, 2009).

efficiency as positive if the article demonstrates a reduction in the workload a caregiving team must invest in managing older adults, therefore increasing caregiver efficiency. These data points show the applicability of the described sensor systems to measure and support daily functioning in older adults living independently at home. We identified *recognized bADLs and iADLs* and *detected changes in activity patterns* when the authors confirmed that their systems permitted the identification of a specific activity, or that an activity pattern change was identified, respectively. These data points identify the effectiveness of sensor monitoring to measure and support daily functioning.

When relevant, article quality was assessed for the risk of bias using the Newcastle-Ottawa Scale by the two reviewers (EL, LN). It accommodates *the variety of nonrandomized study designs*. Differences were resolved by the third reviewer (SK). Zero to 3 stars was considered as low quality, 4–6 stars moderate quality, and 8 or higher was considered as highest quality (Pol et al., 2013).

Data Synthesis and Analysis

Following Pol and colleagues' 2013 article, we replicated their descriptive approach to summarize study characteristics and outcomes, originally chosen *given the heterogeneity of the reporting and designs of the included studies*. Studies were divided into those whose aims were to *measure daily functioning* or *support people in their daily function* (Pol et al., 2013).

Results

Search Results

The searches of PubMed, EMBASE, PsycINFO, INSPECT, and Cochrane databases yielded 761, 3,200, 701, 5,751, and 369 hits, respectively, totaling 10,782. Exclusion criteria could be identified in the titles and abstract of 10,620 articles, retaining 162. Upon full-text review, 149 additional articles were excluded. This process is detailed in Figure 1. Of special note: some articles did not specify subject age, other than "elderly." The reviewers assumed that, unless otherwise specified, "elderly" represents 65 years and older, therefore falling into the inclusion criteria. If a diseased state was not explicitly stated, the reviewers assumed the test sample population did not have significant pathologies and are referred to as *healthy* (Bradford, 2013; Chung et al., 2017; Dasios, Gavalas, Pantziou, & Konstantopoulos, 2015; Suryadevara & Mukhopadhyay, 2014). When articles had multiple age groups with distinguishable data, the data with age group under 65 years were excluded, and the article included.

Quality of the Included Studies

The majority of studies were case studies, considered the lowest on the hierarchy of study design (Ryan, Hill, Prictor, & McKenzie, 2013). Three case–control studies were identified (König et al., 2015; Riboni, Bettini, Civitarese, Janjua, & Helaoui, 2016; Sacco et al., 2012). They obtained 5, 6, and 6 points, respectively, out of a possible 9 on the Newcastle-Ottawa Scale, corresponding to a moderate quality of study (Pol et al., 2013).

Characteristics of the Studies

Table 1 illustrates the characteristics of the 10 case studies and 3 case–control studies. The included articles have a total of 227 subjects, ranging between 1 and 62 participants with a total observation period of 1,262 days, ranging between less than 1 and 730 days.

All three case–control studies were set in experimental lab settings, which had shorter durations of surveillance (15 min, 55 days, and 20 min, respectively), yet larger sample sizes (38, 21, and 38, respectively) (König et al., 2015; Riboni et al., 2016; Sacco et al., 2012). These studies remained focused on demonstrating the viability and reliability of unobstructed sensor recognition of ADL anomalies. One article was set in an assisted living apartment (Galambos, Skubic, Wang, & Rantz, 2013). The studies focused on the role of sensor technology in the *early illness detection model* through the use of sensors to identify changes in activity patterns.

Specific clinical data describing cognitive scores of the sample population are given in three articles (Chung et al., 2017; König et al., 2015; Sacco et al., 2012). The other articles described a lack of specific diagnoses (dementia)

Table 1. General Characteristics of Included Studies

Study	Study design	Participants (numbers)	Age (years)	Setting	Clinical data	Sensor monitoring method	Outcome measure
Studies with the aim of measuring daily functioning							
Bradford (2013)	Case study	20 Healthy	70+	Independent living setting in the community	N/S	Passive sensor network	Some bADL Some iADL (phone use, cooking)
Chung et al. (2017)	Case study	6 Healthy	65+	Independent living setting in the community	bADL, Rosow Breslau Scale, LSA	Passive sensor network	bADL
Dawadi et al. (2013)	Case study	62 Some healthy Some MCI	75+	Experimental lab setting	N/S	Passive sensor network	iADL
Dawadi et al. (2016)	Case study	18 13 Healthy 5 experiencing cognitive difficulties	73+	Independent living setting in the community	N/S	Passive sensor network	bADL iADL (cooking)
Galambos et al. (2013)	Case study	5 MMSE 22–30	69–95	Assisted living apartment	N/S	Passive sensor network, video sensor network	Indirectly bADLs via activity pattern changes
König et al. (2015)	Case–control	38 19 Healthy 19 MCI	65+	Experimental lab setting	MMSE, FAB, iADL, GDS, MADRS, NPI	Video sensor network	iADL, gait
Nef et al. (2015)	Case study	10 Healthy	Elderly	Independent living setting in the community	N/S	Passive sensor network	bADL, iADL
Riboni et al. (2016)	Case–control	21 7 Healthy 14 MCI	Elderly vs 74	Experimental lab setting vs independent living setting in the community	N/S	Passive sensor network	iADL
Sacco et al. (2012)	Case–control	38 19 MCI 19 Healthy	65+	Experimental lab setting	Control = healthy volunteers MMSE, iADL, MADRS, GDS, Level of education	Video sensor network	iADL
Studies with the aim of measuring daily functioning							
Suryadevara and Mukhopadhyay (2014)	Case study	4 Healthy	Elderly	Independent living setting in the community	N/S	Passive sensor network	Some bADL
Tsukiyama (2015)	Case study	1 Healthy	66	Independent living setting in the community	N/S	Passive sensor network	bADL (continence, toileting) iADL (cooking)
Studies with the aim of supporting daily functioning							
Dasios et al. (2015)	Case study	2 Healthy	70+	Independent living setting in the community	N/S	Passive sensor network	bADL, environment (Temp, humidity, light) iADL (cooking)
Lazarou et al. (2016)	Case study	2 MCI	69, 74	Independent living setting in the community	N/S	Passive sensor network	bADL, iADL, sleep quality, physical activity, mood, and social interactions

Note: bADL = basic activities of daily living; FAB = Frontal Assessment Battery; GDS = Geriatric Depression Scale; iADL = independent activities of daily living; LSA = Life Space Assessment of Mobility; MADRS = Montgomery Asberg Depression Rating Scale; MCI = mild cognitive impairment; MMSE = Mini-Mental State Examination; NPI = Neuropsychiatric Inventory Scale; N/S = not specified.

or that neurocognitive and imaging techniques were used to exclude pathologies. Specific details of mathematical algorithms for discussing the detection of ADLs were discussed in only three articles (Riboni et al., 2016; Sacco et al., 2012; Suryadevara & Mukhopadhyay, 2014).

In following inclusion criteria, all articles measured a various selection of ADLs. However, there was no standard of which and of how many ADLs to measure. Only three did not measure iADLs, but rather bADLs (Chung et al., 2017; Galambos et al., 2013; Suryadevara & Mukhopadhyay, 2014). Only Galambos and colleagues (2013) did not specify ADLs, but rather named them *activities of daily functioning*. Analysis of their study did identify various bADLs. König and colleagues (2015) also measured gait; Lazarou and colleagues (2016) measured sleep quality, physical activity, mood, and social interactions.

Characteristics of the Sensor Monitoring Method

Table 2 illustrates the characteristics of the sensor monitoring methods. These were divided into 11 studies with the aim of measuring daily functioning (Bradford, 2013; Chung et al., 2017; Dawadi, Cook, & Schmitter-Edgecombe, 2013, 2016; Galambos et al., 2013; König et al., 2015; Nef et al., 2015; Riboni et al., 2016; Sacco et al., 2012; Suryadevara & Mukhopadhyay, 2014; Tsukiyama, 2015), and 2 studies with the aim of supporting daily functioning (Dasios et al., 2015; Lazarou et al., 2016). Studies with the aim of measuring daily functioning were largely technological developments, and this subset also included two articles investigating its use in clinical practice (Dawadi et al., 2016; Riboni et al., 2016). All articles demonstrated possibilities for clinical practice.

Sensor monitoring methods were largely passive sensor networks. These networks tended to include several different sensor types placed throughout the housing environment: *infrared motion detectors*, *accelerometer (for water flow and bed movement)*, *acoustic sensors*, *humidity sensor*, *pressure sensor*, *reed switches (doors open and close)*, *light sensors (luminescence)*, *temperature sensors*, *bed sensors*, *electricity use sensors*. Two articles described using a single video sensor (König et al., 2015; Sacco et al., 2012) and one a combination of a passive sensor network and a single video sensor (Galambos et al., 2013). The video images were computer processed, allowing for ADL identification. They were also only used in experimental lab settings.

Applicability of Sensor Monitoring

We evaluated applicability as the degree to which sensor monitoring networks measured information relevant to supporting daily functioning. All studies illustrated the applicability of sensor networks as a tool used in clinical practice, able to measure relevant data evaluating cognitive function (*possibilities for clinical practice*; see Table 2). Only the sensor networks from Dawadi and colleagues (2016; CASAS Smart Home), Riboni and colleagues (2016; SmartFABER), Dasios and colleagues (2015; UbiCare), and Lazarou and colleagues (2016; Dem@care) were being used in clinical practice.

Effectiveness of Sensor Monitoring

We evaluated effectiveness as the ability to yield results, the ability to identify changes in ADLs, and to recognize the ADLs themselves. All studies demonstrated the capabilities of their sensor networks to detect changes in activity patterns. These changes, however, appeared to be largely minor fluctuations and limited in time, insufficient to detect cognitive decline indicative of a dementia process. The algorithms used by Bradford (2013), Dawadi and colleagues (2016), Nef and colleagues (2015), Tsukiyama (2015), and Lazarou and colleagues (2016) reliably recognized specific bADLs and/or iADLs. Studies that focused on recognizing ADLs all claimed to do so effectively, although not all reported their accuracy. Only Nef and colleagues (2015) specified the statistical values of the effectiveness of their sensor network. Their study specified an average specificity, sensitivity, and positive predictive value of ADL detection at 96.53%, 68.49%, and 74.41%, respectively. The study looked at one iADL (cooking) and three bADLs (eating, dressing [grooming], and toileting). Watching TV, preparation for bed, stepping, and seated activity were also investigated. Sacco and colleagues (2012) and König and colleagues (2015) further demonstrated that the variation between ADLs of a normal control group and those with MCI can be effectively distinguished. Only Dasios and colleagues (2015) considered safety, and only Lazarou and colleagues (2016) considered the impact of the role of sensor networks on caregiver efficiency.

Discussion and Implications

This systemic review provides an update of the 2013 article by Pol and colleagues whose aim was "to study the application and effectiveness of sensor monitoring to measure and eventually support daily functioning in older people living independently at home." The literature search provided 13 relevant articles since the original article's publication. All studies illustrated the applicability of sensor networks for clinical practice, that sensor networks were effective in detecting changes in activity patterns, and in some studies, identifying specific ADLs. However, the originally identified gap between application in daily practice and effectiveness of support for daily functioning persists. Few systems are being used in clinical practice, and there is little evidence for detecting cognitive decline, as identified by Pol and colleagues (2013). Nevertheless, the sustained publishing of articles confirms the continuing interest of sensor monitoring to measure and support ADLs. We

Table 2. Characteristics of Measurement and Support Studies

Study	Technological development	Clinical practice[a]	Possibilities for clinical practice[a]	Wearable and passive sensors	Passive sensors	Only passive infrared sensors	Diverse binary sensors	Other specific sensors	Number of sensors used	Duration of monitoring	Recognized basic ADLs and instrumental ADLs[a]	Detected changes in activity patterns[a]	Safety	Reduction of hospital days and costs	Professional efficiency[a]
Studies with the aim of measuring daily functioning															
Bradford (2013)	Yes		Yes	Yes	Yes		Yes	Yes	9	N/S	Yes	Yes			
Chung et al. (2017)			Yes		Yes	Yes		Yes	6–9	2 months		Yes			
Dawadi et al. (2013)	Yes		Yes		Yes		Yes	Yes	36	<24 hr		Yes			
Dawadi et al. (2016)		Yes	Yes		Yes		Yes		30	2 years	Yes	Yes			
Galambos et al. (2013)	Yes		Yes		Yes		Yes	Yes	4	2 months		Yes			
König et al. (2015)	Yes		Yes		Yes				1	15 min		Yes			
Nef et al. (2015)	Yes		Yes		Yes			Yes	50	20 days	Yes	Yes			
Riboni et al. (2016)	Yes	Yes	Yes		Yes		Yes	Yes	4	55 days		Yes			
Sacco et al. (2012)	Yes		Yes		Yes			Yes	1	20 min		Yes			
Suryadevara & Mukhopadhyay (2014)	Yes		Yes		Yes		Yes	Yes	84–86	90 days		Yes			
Tsukiyama (2015)	Yes		Yes		Yes		Yes	Yes	4	N/S	Yes	Yes			
Studies with the aim of supporting daily functioning															
Dasios et al. (2015)		Yes	Yes	Yes	Yes		Yes	Yes	9 *nodes*	4 months		Yes	Yes		
Lazarou et al. (2016)		Yes	Yes	Yes	Yes		Yes	Yes	5	4 months	Yes	Yes			Yes

Note: ADL = activities of daily living; N/S = not specified.
[a]See methodology for definition.

discuss the recent technological advances, their applicability and effectiveness, and limitations, and we also provide recommendations for future research in the field.

Technological Advances

Unique network algorithms and designs exist, including the possibility for computer learning to identify behavioral patterns and their alterations. While the choice of analysis algorithm is a crucial component to sensor networks, it falls out of the scope of this article but has been covered by others. Ji and colleagues (2013) and Ryoo (2011) are examples of studies outlining algorithms to identify specific behavior. Trigoni & Krishnamachari (2012) review the algorithms of sensor networks. Network designs continue to be largely made of simple sensors, such as IR motion detectors, reed switches, pressure sensors, or more complicated sensors, such as accelerometer, acoustic, humidity, light, temperature, electricity sensors, and video monitoring systems.

Since Pol and colleagues' (2013) article was published, new technology has emerged, in the form of single video monitoring systems. These systems use a single camera lens to capture a video feed for computer analysis. The simplicity of a single sensor system, as shown by Sacco and colleagues (2012) and König and colleagues (2015), is an advantage to patients and caretakers compared to non-video sensor systems, due to its single component and ease of installation. In comparison, Suryadevara and colleagues (2014) designed a system incorporating up to 86 sensors placed throughout a home, a complicated installation. Video sensing technology also seems to be in its infancy, possibly due to the complicated algorithms required. This is best illustrated by the fact that there were no investigations of its use in an independent living setting in the community. The investigations took place in experimental lab settings (König et al., 2015; Sacco et al., 2012) or in assisted living apartments (Galambos et al., 2013), and did not follow the subjects sufficiently long enough to detect changes in ADL patterns.

Since the Pol and colleagues' (2013) article, a change in research focus has occurred, moving from a focus on technical aspects of sensor monitoring methods to a focus on their capacity to effectively detect or measure activities. Sensor networks supporting functioning have since been little researched, with only two studies, deviating from Pol and colleagues' finding that around half of articles focus on support. This may represent that the technology remains in a developmental stage.

Permanent systems are now in place, demonstrating the feasibility and usefulness of this technology particularly regarding aging in place, such as TigerPlace (Galambos et al., 2013). TigerPlace is an independent living facility that emphasizes research and development of new technology, based on the *aging in place philosophy* (Galambos et al., 2013). This structure consists of 56 independent apartments within a shared building and access to tailored nursing care. They demonstrated that such a system is an effective and convenient way to monitor resident activity (Galambos et al., 2013). They theorized that specific interventions could be individually tailored from their system's observations.

Applicability and Effectiveness of the Technology

Despite the positive applicability and effectiveness that all studies demonstrated in theoretical environments, only 4 articles described systems in clinical practice, and only 2 of the 13 articles specifically aimed to support daily functioning, as compared to half of the studies in the original Pol and colleagues' (2013) article. A disproportionate focus on the technical aspects rather than practical usefulness remains. Furthermore, the studies' methodological shortcomings limit the strength of the evidence for sensor monitoring that measures and supports daily functioning for independently living older adults.

Only Lazarou and colleagues (2016) investigated the use of sensor networks for supporting daily functioning in terms of reducing the workload on caretakers, or other problematic areas such as sleep, physical activity, mood, and social interactions. This was achieved through using a sensor network to tailor optimal interventions and to confirm their outcomes (Lazarou et al., 2016). Their tailored interventions *confirmed significant improvement* over time for ADLs in all their test subjects by focusing on what is clinically relevant (Lazarou et al., 2016).

The technology offers the potential to effectively measure ADLs against time, to identify activity patterns, and their alterations suggesting cognitive dysfunction. This is significant because cognitive impairment occurs on a spectrum with contested boundaries between MCI and progression into dementia (Perneczky et al., 2006). Sacco and colleagues (2012) and König and colleagues (2015) both showed that disturbed iADL patterns can be identified in MCI with their systems. Such an analysis helps identify early and discrete cognitive impairment.

Limitations

Quality

The conclusions in our review are limited by the quality of the studies. The majority are case reports, which are considered the lowest quality of research. There were some moderate quality case–control studies, limited as well due to unclear sample selection criteria with risk for selection bias. By designing more scientifically rigorous trials to investigate the practical usefulness of these monitoring technology, future research could be more innovative.

Choice of ADLs

There was no standard of which bADLs and iADLs were investigated. With this lack of standardization, it is difficult to compare the articles. It is not clear if each category of daily activities must be measured, or whether one or more specific activities yields a higher sensitivity with regards to diagnostic value or longitudinal change. Mioshi and colleagues (2007) found that performance on ADLs will vary between subtypes of dementias, whereas performance on iADLs remains constant (Mioshi et al., 2007). Giebel and colleagues (2015) identified that different ADLs become impaired at different stages of cognitive decline and that impairments in multiple ADLs accumulate as the disease evolves (Giebel, Sutcliffe, & Challis, 2015). The selection of ADLs therefore becomes very relevant. Targeted selection would optimize recognition and measurement of activities that would allow for a general measurement of cognitive function across the various dementias and their subgroups.

Duration of surveillance

The duration of surveillance in most articles was limited to days, or at most, months. Although all studies detected changes in activity patterns, these changes were not due to cognitive decline, but largely to normal fluctuations in activity patterns. The articles did not allow for enough time to successfully measure the progression of neuropsychiatric diseases in clinical practice. It is widely accepted that dementia evolves over months to years. Only Dawadi and colleagues (2016) followed patient evolution over a period of years. Their findings illustrate that machine learning methods may be able to detect behavior routine changes as predictors of clinical scores. They did not identify new cases of dementia within their sample population, which is expected due to the time period of observation and the focus on bADLs. Progression to decreased competence of ADLs is a sign of disease, and iADLs are expected to be the first disturbed. The measurement of bADLs is therefore less relevant in measuring cognitive impairment in the pre-demented population. More surveillance time is necessary to measure changes in ADLs. No studies to date provide this longitudinal perspective.

Location of surveillance

The research focused on independently living individuals associated with minimal cognitive impairment. In this population, a longer time period of observation would be necessary to identify cognitive decline. Ganguli, Dodge, Shen, and DeKosky (2004) identifies a 10%–17% conversion rate to dementia per 2 years of MCI individuals living in the community (Ganguli et al., 2004). Carpenter, Hastie, Morris, Fries, and Ankri (2006) demonstrated that it is possible to measure decreased ADL performance in individuals living in a nursing home with cognitive impairments over a 90-day period (Carpenter et al., 2006).

Lack of clarification of ADL identification accuracy

Most studies did not address the accuracy of activity identification. There was little description of what constituted effective recognition. Dawadi and colleagues (2013) sensor network was found to be a class better *than random*, yet sufficient to be effective (Dawadi et al., 2013). Nef and colleagues (2015) quantifies average specificity (96.53%), sensitivity (68.49%), positive predictive value (74.41%), and F-measure (71.33%) when compared to direct observation (Nef et al., 2015).

Data collection, processing, and information presentation

There is little information in the reviewed studies on how sensor monitoring data were collected, processed, and displayed to the end users. Data management plays a crucial role in the usability of sensor networks. Future studies should comment on this.

No elaboration of effects on somatic complications

No article elaborated on the outcomes of sensor monitoring on somatic disorders, such as delirium. Such capabilities would be significant. There is a 14% point prevalence of delirium among adults over age 85 living in the community (Folstein, Bassett, Romanoki, & Nestadt, 1999). Changes in activity patterns are a clinical sign of delirium. A sensor network could provide a more rapid identification. Other possibilities of detection are more progressive complications such as weight loss following difficulties cooking.

No elaboration on the acceptation of monitoring technology or on privacy perspectives

Other than Chung and colleagues (2017), the question of acceptance and privacy perspectives of sensor monitoring systems was not investigated. A lack of acceptation may hinder its incorporation among older adults (Boise et al., 2013). Despite increasing the perceived level of safety, family members' reassurance, and family access to up-to-date health status information, monitoring systems invoke feelings of privacy infringement (Boise et al., 2013; Chung et al., 2017; Lie, Lindsay, & Brittain, 2016). Lie and colleagues (2016) argue that there is a risk of creating stereotypes of excessive frailty through the marketing of such devices. Chung and colleagues (2017) identify that the majority of their test subjects perceived that sensor-based monitoring would be useful, yet had mixed opinions about privacy concerns (Chung et al., 2017). Boise and colleagues (2013) showed that the cognitively impaired older adults were more likely to accept sensor monitoring.

Recommendations for future research

In considering the limitations identified in this review, the following recommendations can be made:

1. Identification of selected bADLs or iADLs, targeted to best identify cognitive dysfunction.
2. Periods of observation sufficiently long to observe cognitive fluctuations and the natural evolution of cognitive impairment.

3. Improve quality through well-planned case-controlled studies including an a priori defined level of detection accuracy deemed of practical usefulness.
4. Consider description of system data collection, processing, and information presentation to end users.
5. Consider the somatic benefits of sensor networks.
6. Consider the acceptance of such technology among older adults.

Future research could consider these limitations and recommendations.

Conclusion

Since the original Pol et al. (2013) article was published, 13 new studies have been published supporting the application and effectiveness of sensor monitoring to measure and eventually support daily functioning in older adults living independently at home. These systems, using a variety of wireless passive sensors and algorithms, provide the possibility to recognize ADLs and identify changes in activity patterns, likely sufficient for clinical use. However, these studies do not confirm clinical applicability. Current research remains unanimously positive towards the potential for effective clinical use, as Pol and colleagues concluded, despite limited quality of available research, lack of targeted ADLs, short duration of research, lack of ADL identification accuracy, no investigation of potential somatic benefits, and a lack of investigation on the acceptability of the technology. There remains too much focus on technological usefulness, and practicality still needs to be established.

Supplementary Material

Supplementary data are available at *The Gerontologist* online.

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Conflict of Interest

None reported.

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