Bachelor Thesis in Health Psychology and Technology

The state of the art of the technologies that monitor disease progression in dementia patients: A scoping review

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Abstract

Background

The aging of the society causes an increase in dementia patients around the world. A challenge arose about ways in which people with dementia can maintain living in their own homes for as long as possible. The limited capacity of elderly living and the desire of most elderly to live independently are causing researchers to develop home-based solutions. Technologies that monitor the disease progression by detecting symptoms have been developed since the current decade. However, there is no global enthusiasm because therapists have limited understanding of the added value and technologies have several limitations such as a lack of user-centered designs. Researchers who aim to develop new technologies may benefit from evaluations of existing technologies. Therefore, the primary purpose of this study was to identify current literature on technologies available to monitor behavioural and emotional symptoms in people with dementia. In addition, the research questions involves an evaluation of types of technologies, types of monitored symptoms, the operationalization of the data, and the (dis)advantages. With this, the state of the art in the development of monitoring technologies could be determined.

Methods

A literature review was conducted in Scopus database. Eleven studies were included on the basis of in- and exclusion criteria. Information in the studies that adds up to one of the research questions was extracted.

Results

The results showed that activities of daily living, agitation, walking behaviours, pain, and stress were main focus to monitor disease progression. This was monitored with the use of wireless sensor networks, wearable devices, Kinect sensor networks, and a mobile app. Most of the raw data was processed by algorithms. As a disadvantage, it appeared that the user-friendliness of the wearable devices was insufficient in terms of number of mounted devices, size of the device, and required help with (un)mounting the device. Moreover, the feasibility of wireless sensor networks demonstrates limitations because the systems cannot distinguish between movements of the resident or visitors. In addition, a major limitation of the technologies is that the majority was not tested upon reliability, and none of the technologies was evaluated upon degree of privacy invasion.

Discussion

Though some devices seemed promising, all the devices revealed shortages. Future researchers of technologies should consider a decent validity and reliability investigation, as well as a privacy evaluation because it turned that privacy concerns are an unsolved topic. Moreover, the extent to which emotional symptoms can be detected is small. Although it might be difficult to monitor, dementia changes emotional well-being even in the early stages. Thus, continuously monitor emotional symptoms will show changes perhaps before other symptoms will appear.

Keywords: aging problem, dementia, technology, monitoring

Introduction

Problem identification

Dementia is a mental illness which affects a growing number of older adults around the world (Khan, Ye, Taati, & Mihailidis, 2018). Among the Dutch population, there are currently 270,000 people diagnosed with dementia. The number of people suffering from this disease is likely to reach half a million people within the next twenty years (Alzheimer Nederland, n.d.). Dementia is a neuro degenerative disease, of which Alzheimer's disease is the most common cause and type (Alzheimer Nederland, n.d; Griffiths & Rooney, 2006). Dementia emerges mostly at an older age and appears with a characteristic progression and typical phenomena (Reisberg, Ferris, de Leon, & Crook, 1982). The cognitive decline involved in dementia affects the ability of people with dementia (PwD) to maintain the activities that daily living requires (Urwyler et al., 2017). Symptoms associated with dementia are for example apathy, irritability, depression, agitation, anxiety, worsening motor activity, delusions, and sleep disorders (García-Alberca, Lara Muñoz, & Torres, 2010; Vogel, Waldorff, & Waldemar, 2010).

The number of people that will be diagnosed with dementia is increasing. This is part of the ageing problem, that can be interpreted as an increase in the percentage elderly people in the society. This causes challenges in the elderly health care. Patients in the early stages of dementia are often capable of remain living on their own, but as the disease progresses residence within an institution may be required. Due to the ageing problem, an increasing number of elderly people with dementia are being required to move into institutions. However, the ageing problem has also caused a shift in the job market because there are relatively fewer working-age people. This makes it impossible to care for all those in need of help within care institutions (Alzheimer Nederland, n.d.). Moreover, a disadvantage of placement in care facilities is that such placements are associated with elevated levels of social isolation, depression, and overall mortality risk, especially when they occur against the wishes of the patient (Aneshensel, Pearlin, Levy-Storms, & Schuler, 2002).

Consequently, as the number of PwD in the population rapidly increases, the medical system face challenges to find ways in which PwD are able to remain living safely and independently in their own homes. Accurate disease monitoring can be regarded as a key factor in organising healthcare for a PwD in a safe and desirable way. To this end, while many measurements have been developed to monitor disease progression, they have disadvantages that can potentially be solved with the use of advancing technologies. A major setback of the

assessment of disease progression nowadays is that it is performed periodically following a diagnosis. However, multiple studies confirm the low rates of clinical assessment and diagnosis in primary care with regard to dementia (Boise, Neal, & Kaye, 2004). Cognitive testing is not a routine procedure when an elderly person visits their general practitioner (Hayes et al., 2008). This means that dementia is frequently initially, or even completely, unrecognized by general practitioners. After a diagnosis is established however, the progression of the disease is monitored by episodically executing interviews or through questionnaires given to the patient and caregivers. (Finkel, 2001).

Conventional methods of monitoring disease progression

Currently, mainly patient or caregiver based questionnaires are used by professionals. A literature review by Clare, Marková, Verhey, and Kenny (2005) concerning the methods and instruments used to measure awareness in PwD revealed that there are five categories of assessment approaches. One of these categories consisted of analysing interviews and conversations. The other four methods where all focussed upon retrieving information with the use of questionnaires, namely clinician rating methods, questionnaire-based methods, performance-based methods, and multidimensional methods. The findings from the literature review by Clare et al., (2005) illustrated that measurements to explore one aspect of dementia often include episodically executed questionnaires.

Questionnaires, however, differ in their degree of quality. According to Sikkes, De Lange-de Klerk, Pijnenburg, and Scheltens (2009) questionnaires in measuring activities of daily living (ADL) can be very helpful for diagnosing dementia and are often used by clinicians. However, only two of the twelve questionnaires, namely the Bristol ADL and the Disability Assessment for Dementia, were classified as being of moderate quality in regard to several measurement properties. The Bristol ADL is a carer-based questionnaire concerning a person's ability to maintain normal daily living activities such as eating/drinking, dressing, finances, hobbies, and hygiene. A total of 20 daily living activities are covered with the Bristol ADL scale and according to users it is short and easy to use (Bucks, Ashworth, Wilcock, & Siegfried, 1996).

A common dementia symptom in addition to changes in ADL is the presence of agitation. Agitation can be defined as including inappropriate vocal, verbal, or motor activities that cannot be explained by environmental factors or medical problems (Cohen-Mansfield & Billig, 1986). Most PwD experience this symptom during the course of their disease. Moreover, it is often these agitated behaviours that result in placement in long-term care

settings (Bankole et al., 2012). One of the most frequently used questionnaires for assessing agitation is the Cohen-Mansfield Agitation Inventory (CMAI). This caregiver-based instrument focusses on the frequency of agitation, physical aggression, and verbal aggression. The CMAI is completed in a face-to-face interview between a professional care worker and informal- or professional caregiver and takes approximately 20 minutes. Scores can be between (1) = never and (7) = several times an hour (Cohen-Mansfield, 1997).

The usage of the Mini Mental Stage Examination (MMSE) is also widely accepted, and measures cognitive performances (Creavin et al., 2016). As dementia is associated with a cognitive decline, many clinicians use this short screening tool. However, a golden standard threshold does not exist, and different thresholds serve different sensitivity and specificity. Most of the studies in the literature review conducted by Creavin et al., (2016) used a cut-off score of 24 to confirm or reject a dementia diagnosis. This threshold has a sensitivity score of 0.85 and a specificity score of 0.90. The authors concluded that the MMSE should not be used as stand-alone tool to either confirm or exclude dementia. The suggestion of the authors of a similar literature review reported that clinicians should conduct additional tests besides the MMSE before making a diagnosis (Arevalo-Rodriguez et al., 2015). It has also been found that the results of the MMSE correlate positively with scores from the Bristol ADL (Bucks et al., 1996).

Clearly, validated rating scales are helpful tools for the diagnosis, assessment, and monitoring of dementia disease as they provide a snapshot of an individual's abilities and disabilities. Nonetheless, these standard rating scales do not capture the complexity of the illness (Romdhane et al., 2012). Firstly, the early signs of cognitive impairment are difficult to detect, because individuals and their family members may be unaware of their impairment. Moreover, cognitive and motor functioning are thought to naturally decrease as people age Consequently, cognitive tests are not executed. The second limitation of conventional measurement methods is that their episodically timeframe reflects a single snapshot of a performance that might be confounded by many aspects, such as how a patient is feeling on that day. For this reason, periodic test scores may not reflect true changes but rather measure variability in behavioural or emotional symptoms. Conversely, continuous assessment reveals a realistic and true pattern of disease progression, rather than a reliance upon detached observations (Hayes et al., 2008).

A third disadvantage of scales such as questionnaires are reliability biases. The subjective opinion of patients and their caregivers may influence the results. A person with dementia may behave differently in the presence of others than when he or she is alone. There

is also the fact that the completion of these scales is both human and time intensive. In this regard, in recent years, technologies have been designed that automatize the proceedings in the healthcare. Kaye et al., (2008) suggests that methods of continuous sensor monitoring represent a reasonable adjunct to conventional approaches to monitoring meaningful changes in disease progression. In this way, a combination of episodically measurement by existing scales and continuously monitoring by means of technology enables healthcare providers to adjust the offered care to the needs of the dementia patient.

Monitoring disease progression with the use of technology

In undertaking the continuously monitoring of PwD, such monitoring can be focussed upon, for instance, symptom progression in terms of behavioural and emotional patterns, medicine intakes, and falls (Brownsell, Bradley, Bragg, Catlin, & Carlier, 2002). The placement of sensors in the homes of the elderly who may potentially develop dementia can be helpful for early recognition of the disease. Early detection of dementia is not only beneficial for the patient but also for the patient's family. Early diagnosis provides PwD the opportunity to consider and form their own decisions regarding the care planning process (Bradford, Kunik, Schulz, Williams, & Singh, 2009). In addition, when a diagnosis of dementia has been established a pharmacological intervention may slow down the process of cognitive decline (Standridge, 2004). This, in turn, plays a critical role in the maintenance of a patient's independence. Thus, the detection of the first signs of dementia and monitoring the progression of the disease in a continuous manner can be facilitated by a sensor system placed in the homes of PwD. This is more time-efficient and accurate than the conventional methods used for monitoring the symptoms of dementia presented in the previous section.

Although the technologies designed for these monitoring purposes are relatively new, intelligent devices have begun to be utilised within healthcare in recent years. Safety detection and monitoring biological rhythms such as sleep quality and quantity are a couple of purposes that these technologies are able to serve (Fowler, Kott, Wicks, & Rutledge, 2016). Fall detecting sensors have been widely accepted and provide the elderly with an increased sense of safety and independence (Abbate et al., 2012). A three-year pilot study in Finland using safety technologies demonstrated that PwD were able to live, on average, eight months longer in their own homes before moving to a care institution (Riikonen, Mäkelä, & Perälä, 2010).

According to Caulfield (2013), the use of in-home sensors is one form of 'Connected Health', that is, in-home sensors provide the ability to care for a person without actually being

in his or her proximity, which may be helpful, for instance, for the caregivers of people with certain illnesses. The stakeholders, including professional care workers and informal caregivers, are connected by means of timely sharing of accurate and pertinent information regarding the patients through the clever use of devices, communication platforms and people (Caufield, 2013).

Consequently, the acquisition of health-related data from the individual concerned makes it possible for health care employees and caregivers to be informed at a distance. This may have enormous potential with regard to alleviating care burdens. Seventy percent of the PwD in the Netherlands live independently in their own homes with the help of caregivers (Alzheimer Nederland, n.d). Those are professional home care workers, but also informal caregivers, such as spouses, children, other family members, and friends. Around 350,000 informal caregivers provide an average of 20 hours unpaid care for people with a form of dementia (Jansen, Werkman, & Francke, 2016). According to Jansen et al., (2016), more than half (52%) of the informal caregivers experience a high care burden. Accordingly, these informal caregivers of PwD are at higher risk than other patient groups caregivers of feeling overwhelmed and depressed (Eales, Kim, & Fast, 2015). Yet, owing to the ageing problem, there will be an increase in the number of caregivers that are required. For this reason, it is extremely desirable to lower the care burden

Another reason why technologies in the environs of PwD can be helpful is the sense of independence. Elderly people consider it very important to be able to live independently. Ninety-four percent of the elderly in the Netherlands desire to live independently in their own homes for as long as possible (Nederlandse zorgautoriteit, 2018). In a trial of an intelligent monitoring system, Sixsmith (2002) revealed the opinions of the users of the in-home sensor system. Eighty percent of the elderly and caregivers were satisfied with the system. The elderly indicated an enhanced sense of safety and security and they thought that their sense of independence increased. Moreover, two studies revealed that a home sensory system did not cause users concerns regarding their privacy (Wild, Bois, Lundel, & Foucek (2008); Steele, Lo, Secombe, & Wong (2009). The use of sensors as unobtrusive monitoring devices are preferred rather than placing cameras or issuing wearable devices due to the privacy and user-friendliness they afford (Gochoo et al., 2019).

To this end, one of the tasks that care workers and informal caregivers need to perform, is to keep track of the progression of the disease, hence, the technological automatization of the monitoring of the disease progression should solve part of the care

burden problem, may enhance a sense of safety and independency, and may also extend the period that PwD can remain living in their own homes.

Gap in the knowledge

New technologies which continuously monitor dementia-related symptoms by means of an in-home sensor system may extend the time a person can remain at home and may also provide peace of mind to informal caregivers. However, according to Australian research conducted by PwD therapists, there is a limited understanding of the available technologies. Moreover, the awareness of how assistive technology can be used is limited and therapists state that they experience barriers in identifying and providing appropriate technologies for PwD (Jarvis, Clemson, & Mackenzie, 2017). In addition, a literature review by Neubauer et al., (2018) on technologies that detect wandering behaviour in PwD stated that the majority of the technologies lacked usability testing and user-centred designs. Moreover, the authors questioned the accuracy of the designers' claims regarding the effectiveness of the technologies and they found standard sets of descriptors through which to compare technologies do not exist. For this reason, therapists and other care workers may struggle to determine the right device for their patient, as it is hard to compare multiple device types and whether single or multiple device types such as GPS and Bluetooth systems are preferable.

In order to create support for an in-home sensory monitoring system for PwD the technology should be helpful and comprehensible by all the stakeholders, including the patients, the informal stakeholders, and the professional staff from care institutions, such as therapists. In designing new monitoring devices, it may be informative to know the working mechanisms and advantages and disadvantages of contemporary monitoring systems. Accordingly, an examination of the state of the art in the development of this new branch is likely to reveal important information for researchers willing to develop a sensor system that is both reliable and valid.

Therefore, the aim of this study is to identify the current literature on the technology available to monitor behavioural and emotional symptoms in PwD. As such, the following questions are formulated:

RQ 1: What types of technologies are used to monitor behavioural or emotional symptoms in PwD?

RQ 2: What are the behaviours and emotions that technologies to monitor behavioural or emotional symptoms in PwD target?

RQ 3: How are the data from technologies to monitor behavioural or emotional symptoms in PwD operationalised?

RQ 4: What are the advantages and disadvantages of technologies that monitor behavioural or emotional symptoms in PwD?

Methods

The review aimed to identify peer-reviewed studies concerning the technologies that have been developed to monitor behavioural or emotional symptoms in PwD. The process of identifying appropriate studies consisted of a consecutive step-by-step plan. Firstly, the scope of the review needed to be determined.

Scope:

The scope of this review was determined by using the PICOC-framework (Petticrew & Roberts, 2008), which consists of five parameters:

- Population: patients with dementia or a related disease such as AD.
- Intervention: empirical studies focused on one or multiple methods to monitor behavioural or emotional changes in PwD.
- Comparison: dementia patients in-group, between groups, or compared to healthy control subjects.
- Outcome(s): sensor or monitoring systems used or tested to monitor behavioural or emotional symptoms belonging to dementia.
- Context: out-care dementia patients or institutionalised patients.

Search strategy:

The literature in one database was searched, namely Scopus. This database was searched using MeSH (medical subject heading) terms identified as Set 1: dementia OR Alzheimer OR disease OR illness, and Set 2: techn* AND in-home OR monitor AND symptom OR behavio* OR emotion

The general strategy was to search title Set 1 plus title, abstract and keywords Set 2. This was entered into Scopus database, resulting in: TITLE(dementia OR alzheimer OR disease OR illness) AND TITLE-ABS-KEY(techn* AND in-home OR monitor AND symptom OR

behavio* OR emotion) AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"cp") OR LIMIT-TO (DOCTYPE,"re") OR LIMIT-TO (DOCTYPE,"ip")) AND (LIMIT-TO (SUBJAREA,"MEDI") OR LIMIT-TO (SUBJAREA,"COMP") OR LIMIT-TO (SUBJAREA,"NEUR") OR LIMIT-TO (SUBJAREA,"ENGI") OR LIMIT-TO (SUBJAREA,"CHEM") OR LIMIT-TO (SUBJAREA,"NURS") OR LIMIT-TO (SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"AGRI") OR LIMIT-TO (SUBJAREA,"HEAL")) AND LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2000-2018) AND (LIMIT-TO (LANGUAGE,"English")).

With this search string, papers older than those published in year 2000 were excluded. This was decided because it is thought that new technologies provide a realistic view of the contemporary situation and because the use of technology for monitoring disease progression is relatively new. For those reasons, it was expected that a considerable number of studies would have been published from 2000 onwards. Papers from the subject area of biochemistry, papers not written in English, and book chapters were also excluded.

Study selection:

The search for finding relevant articles involved five steps and was executed in April, 2019. The first step in the study selection process was to remove any duplicates. Then, the studies were be scanned at title and abstract level. The title, keywords, or abstracts had to at least include a type of technology; this could be the name of a device or a description including smart-home system, unobtrusive technology, or technology. Moreover, the abstract had to include the population. Studies whose participants were not dementia-related patients were excluded in this phase. As a third step, the full texts of the remaining papers were going to be read and assessed.

Studies were included if (a) the population were dementia patients or had a related disease such as Alzheimer patients; (b) the study was empirical and addressed the use of technology to monitor behavioural or emotional symptoms; (c) an observation or comparison between- or in-group was executed; (d) the outcomes were a set of monitored behaviours or emotions; and (e) the participants of the study were either institutionalised, or lived alone orr accompanied in their own homes. These inclusion criteria were determined on the basis of the PICOC framework. The final step of the study selection process consisted of scanning the reference lists of the already included studies to find additional studies that were not found with the search string in Scopus.

Data extraction:

For each included study, part of its content may or may not have been extracted. In order to be able to answer the research questions, the researcher extracted multiple parameters. The first set of parameters consisted of the main characteristics of the studies (Table 1).

Table 1

Data extraction of components that provide a general overview of the studies

Parameter	Data to be abstracted
Authors	Name of the authors who conducted the study. Only the first author is used in this literature review. The rest of the authors are indicated with 'et al.'.
Year of publication	Year of publication of the study.
Location of the research	Indicated either by the name of the city or country, depending on availability.
Number of participants	Number of participants (N) as reported by the researchers.
Design	Chosen study design e.g. cohort study, cross-sectional. Either reported in the study itself or assessed by the researcher of this literature review.
Population	Refers to the phase of the disease. Participants reported as having mild cognitive impairment were classified as early stage dementia. Participants reported as dementia patient were classified as middle stage dementia. Institutionalised participants were reported as late stage dementia. Other participant groups were (healthy) control subjects.
Observation environment	Indicates whether the technology was tested in the homes of the participants (natural), in a pre-designed laboratory room (labroom), or in a hospital.

The second set of parameters was focussed on several features of the technologies and it's usage in the study (Table 2).

Table 2

Data extraction of the components that provide the features of the technologies used

Parameter	Data to be abstracted
Type of technology	The type of technology, e.g wireless systems, wearable devices, GPS.
Behaviour	Detection purpose of the technologies to detect, e.g walking, agitation.
Duration	Number of minutes, hours, days, or weeks that the technology monitored one single participant.
Name of technology	Refers to a name of the technology if available.

Equipment	Refers to the components of the technology, e.g wristband, or an X amount of wearable nodes.
Observation environment	Indicates whether the technology was tested in the houses of the participants (natural), in a pre-designed laboratory room (labroom), or in a hospital.

The third set of extractions consisted of information, reported by the researchers of the studies, that could be regarded as an advantage or disadvantage of the technology (Table 3).

Table 3

Data extraction of advantages or disadvantages of the technology

Parameter	Data to be abstracted
Validity	Refers to the extent that the technology measures what it proposes to measure. This was by some researchers reported using Pearson's correlation test. (+) means that the researchers reported positive findings about forms of validity, for example a Pearson's correlation of at least $r = .60$, or a comparison with a conventional scale with a p-value equal or smaller than 0.05. (-) means that the researchers reported negative findings about forms of validity. It might be that the researchers reported no correlation in the results between the different elements of their technology or between their technology and conventional scales. (N/A) means that nothing about validity was reported
Reliability	Refers to the extent that the reliability of the technology was sufficient. The technology must produce consistent and stable results. This was by some researchers reported using Cronbach's alpha. (+) means that the researchers reported positive findings about the reliability of their technology, for example by a Cronbach's alpha of at least $\alpha = .70$, or by a reported sufficient level of reliability otherwise. (-) means that the researchers reported negative findings about the reliability of their technology (N/A) means that nothing about reliability is reported
Automatizing	Refers to the extent that humans need to enter data, with the exception of installation phases and data processing phases (+) means that the technology works without assistance by humans (-) means that assistance is needed for the technology to work
Unobtrusiveness	Refers to the level of unobtrusiveness of the technology. This is defined as the degree to which a device is noticeable, conspicuous, cumbersome, annoying, or draws attention. This includes the degree of visibility, degree of comfortability, and user-friendliness

	(+) means that the researchers reported predominantly positive findings regarding unobtrusiveness
	(-) means that the researchers reported predominantly negative findings regarding unobtrusiveness
	(N/A) means that the researchers did not report anything about unobtrusiveness
Feasibility	Refers to the level of feasibility of the technology. This refers to how conveniently a type of technology can be installed, the complexity of the technology and involved costs
	(+) means that the researchers reported predominantly positive findings about the feasibility of the technology
	(-) means that the researchers reported predominantly negative findings about the feasibility of the technology
	(N/A) means that the researchers reported nothing about feasibility
Privacy	Refers to privacy concerns. This may be concerns about feelings of being watched, or sensitive data distribution
	(+) means that the researchers reported only positive findings about privacy
	(-) means that the researchers reported at least one negative finding about privacy
	(N/A) means that nothing about privacy was reported

Notes: Advantages are indicated with (+), disadvantages are indicated with (-), while (N/A) means not available.

Results:

Description of the studies.

The titles and abstracts of 61 studies were identified as potentially relevant after assessing 230 studies found on the Scopus database (Figure 1). After reading the full text, a total of nine studies were included in this literature review. An additional search through the literature lists of these studies added another two studies. According to the predefined requirements, a total of 11 studies met the criteria and were included in this review. Although studies from year 2000 till 2019 were included, the oldest study was published in 2007 (Table 4).

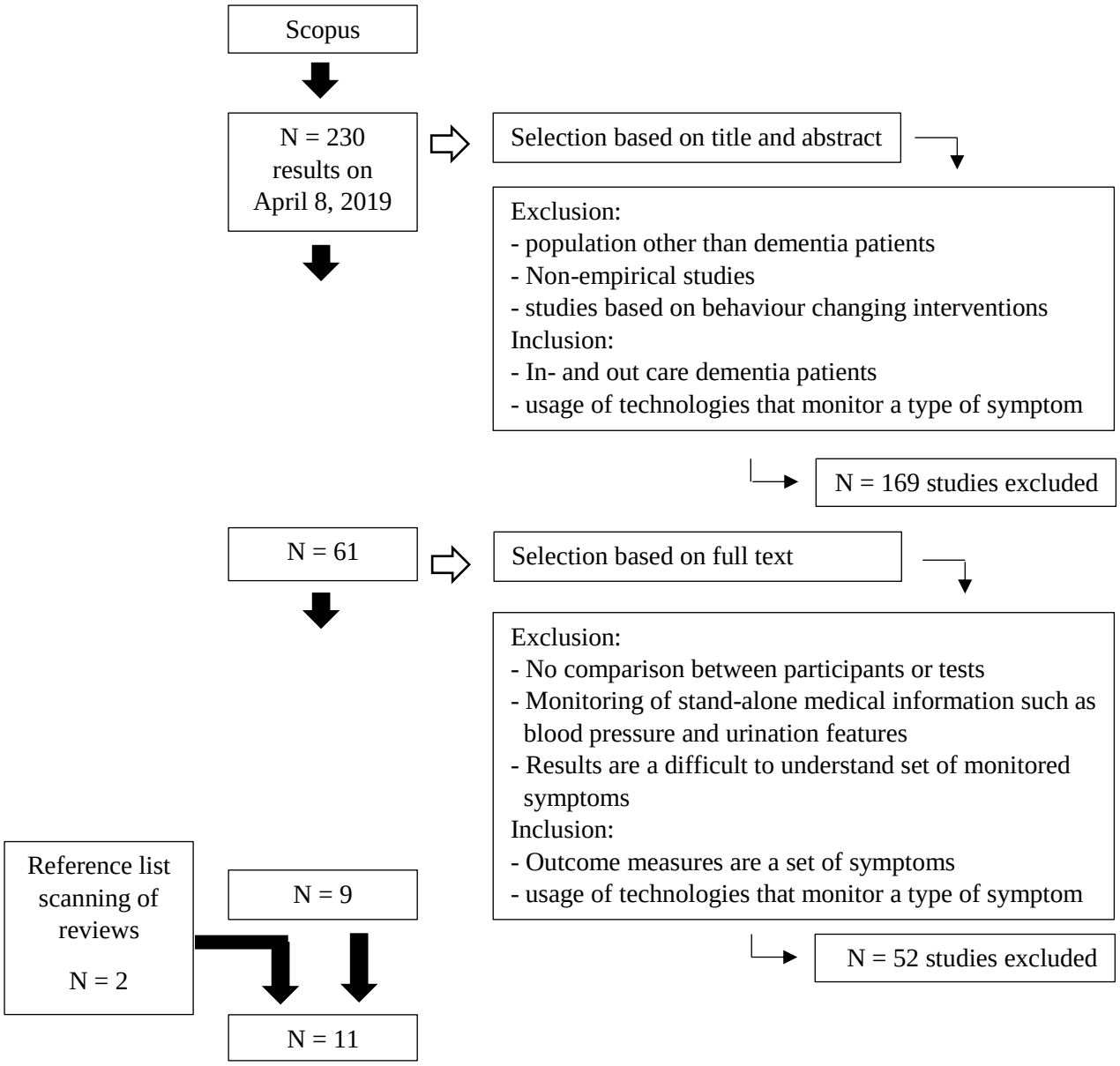

Figure 1. Flowchart of study selection.

Five of the studies described wearable devices [3,4,6,7,10], three of the studies described a technology with wireless sensors [1,2,8], two of the studies made use of Kinect sensors [5,11] while one study used a mobile application (app) [9]. All the studies were designed to monitor the specific behaviour that PwD exhibit. Although different researchers gave different names to the behaviours, the types of behaviours can be divided in ADL [1,2,5,8], agitation [3,6,10], walking [2,4,11], and sensations [7,9]. The number of participants in the studies varied between n = 6 to n = 183. The mean age of the participants was 80 years, in a range from 59 to 94 years. All the studies included dementia patients, of which three studies specifically concerned AD patients.

Table 4

Study characteristics ranked by year of publication

Study number	Author	Year	Location	N	Design	Population	Observation environment
1	Suzuki	2007	Japan	14	Cohort study	Early stage dementia (n = 4), HC (n = 10)	Natural
2	Hayes	2008	Portland	14	Cross-sectional	Early stage dementia (n = 7), HC (n = 7)	Natural
3	Bankole	2012	Roanoke	6	Quasi experimental	Late stage dementia (n = 6)	Natural
4	Hsu	2014	Taiwan	71	Quasi experimental	Middle stage dementia (n = 21), HC (n = 50)	Labroom
5	König	2015	Nice	49	Quasi experimental	Early stage dementia (n = 23), dementia (n = 12), HC (n = 14)	Labroom
6	Valembois	2015	France	183	Cross-sectional	Middle stage dementia (n = 126), control subjects (n = 57)	Hospital
7	Kikhia	2016	Sweden	6	Quasi experimental	Late stage dementia (n = 6)	Natural
8	Urwyler	2017	Bern	20	Cohort study	Middle stage dementia (n = 10), HC (n = 10)	Natural
9	Atee	2017	Perth	40	Quasi experimental	Late stage dementia (n = 40)	Natural
10	Nesbitt	2018	Norfolk	8	Pilot study	Late stage dementia (n = 8)	Natural
11	Dolattabadi	2019	Toronto	20	Cross-sectional	Late stage dementia (n = 20)	Natural

Notes: HC = Healthy Controls. The controlled studies observed their participants in a predesigned experimental room, while the natural observation type means an observation undertaken in the natural living circumstances of the participants.

Five of the studies involved healthy elderly as a control group. The dementia patients in five studies were institutionalised, four studies reported that their participants lived independently, and two did not report the living situations. While the majority of the studies were executed in natural living environments [1-3, 7-11), two studies conducted their experiments in a simulated environment [4,5], and one study was performed in a hospital [6]. The participants in Study [6] were admitted to a hospital for at least ten days due to infectious diseases, heart diseases, falls, or other causes.

RQ 1: What types of technologies are used to monitor behavioural or emotional symptoms in PwD?

The included studies made use of four different types of technology, namely wireless sensor networks [1,2,8], wearable devices [3,4,6,7,10], Kinect sensors [5,11], and a mobile app [9] (Table 5). Wireless sensor networks were specified as wireless infra-red sensor networks [1,2]. Wireless sensors were installed at multiple places in the houses of the participants, while a central computer was placed to automatically retrieve the data [1,2,8]. The sensors were activated by human heat within an area of five meter from the sensor [1], but also humidity sensors, luminescence sensors, presence sensors, and acceleration sensors were all apparatus within the sensor boxes [8]. A wireless system can also consist of passive infrared pyro electronic motion sensors to detect body movement, magnetic contact sensors to detect door movements, and motion sensors to detect walking [2].

A second type of technology to monitor the behavioural or emotional symptoms of PwD were wearable devices [3,4,6,7,10]. Wristbands [3,6,7,10] or shoe- and belt- mounted sensors were a main part of this equipment [4]. All the devices were composed of accelerometers that measure limb movements. These were specified as a triaxial accelerometer [4,10], three axes of linear accelerometers performing full rotational and translational sensing [3], and a high sensitivity accelerometer [6]. The technology within the experiment in Study [4] was further composed of a uniaxial gyroscope, a biaxial gyroscope, a microcontroller, and a micro-SD flash memory card to store the data. The data from the wearable devices could also be transmitted to a computer through a wireless network [3,6,10] or transmitted through radio waves [7].

Table 5

Characteristics of technologies that monitor behavioural or emotional symptoms in dementia patients

Study number	Author	Technology type	Behaviour	Duration	Name of technology	Equipment
3	Bankole	Wearable device	Agitation	9 hour	Body Sensor Network	Three body mounted nodes
4	Hsu	Wearable device	Walking behaviour	*	N/A	Three body mounted nodes
6	Valenbois	Wearable device	Agitation	10 days	N/A	Wrist actigraph
7	Kikhia	Wearable device	Sensation	24 hour	DemaWare@NH: Philips sensor DTI-2	Wristband
10	Nesbitt	Wearable device	Agitation	8 hour	N/A	Wristband and mobile android phone
1	Suzuki	Wireless system	Daily activities	Mean of 78 days	N/A	Five infrared sensors
2	Hayes	Wireless system	Daily activities + walking behaviour	26 weeks	X-10 wireless sensors	Infrared motion sensors, magnetic contact sensors, motion sensors
8	Urwyler	Wireless system	Daily activities	20 days	N/A	10 boxes, each consisting of five sensors
5	König	Kinect sensor	Daily activities	35 minutes	Event Monitoring System	Color-depth Kinect sensors
11	Dolatabadi	Kinect sensor	Walking behaviour	28 days	AMBIENT	Kinect sensor, RFID tags, antennas
9	Atee	Mobile app	Sensation	13 weeks	ePAT: electronic pain assessment tool	Mobile android phone

Notes: Duration = monitoring duration is per subject. *= participants in this research were observed during a single-task walking and a dual-task walking, and during eight balance tests. N/A = not available.

Kinect sensors were reported in two studies. An AMBIENT (ambient mobility, balance, and gait evaluation and monitoring technologies) setup [11] and EMS (event monitoring system) [5] were chosen by the researchers. Both worked with Microsoft Kinect sensors. The colour-depth Kinect sensors tracked human movement in the proximity of a specific object causing the system to automatically detect a type of behaviour, for instance the watering of a plan [5]. Radio-frequency identification (RFID) tags needed to be mounted by the participants to enable the Kinect sensors to identify the movements of the resident [11].

The fourth and last technology which was observed in the selected studies was a mobile app called the electronic Pain Assessment Tool (ePAT) [9]. This is a facial recognition technology that detects facial micro-expressions indicative of pain. The android app assesses a map of a patient's face within ten seconds.

RQ 2: What are the behaviours and emotions that these technologies target?

The monitored behaviours and emotions can be divided into ADL [1,2,5,8], agitation [3,6,10], walking [2,4,11], and sensations [7,9]. The next section includes a description of these behaviours and a description of the validity and reliability of the parameters for the behaviours. The main results of the monitored data of the technologies are also discussed.

Activities of daily living

This category of behaviours is attempted to measure according to active periods in general [1,2] or the duration and amount of specific daily activities [5,8]. The mean number of firings per minute in the periods of a participant being in their home indicate a day-to-day pattern of activity [2]. The mean number of firings was also used to calculate the number of outings per month and sleep interruptions per day [1]. In addition to these parameters, bedtime and wake-up time were detected by the sensors in order to calculate sleep time and sleep rhythm. Contrasting with these purposes, cataloguing of many different ADL such as watching television, grooming, toileting, and eating were detected by the technology [8]. The beginning and end times of the activities and mean minutes per activity over a period of 20 days were monitored and calculated. This allowed the researchers to detect changes in daily routines. Similarly, the number of minutes and the number of initiated and completed activities were the main interest of a controlled experiment [5]. Example activities were preparing tea,

reading an article, or preparing medication.

Sufficient validity was found for three of the technologies [1,5,8] (Table 6). The results from the EMS correlated positively with scores from MMSE, Frontal Assessment Battery, Free and Cued Selective Reminding test, and Instrumental Activities of Daily Living screening for Elderly (Spearman's correlation coefficient $p = < 0.05$) scales, but not with the Narcissistic Personality Inventory ($p = 0.234$) in initiated activities [5]. The system used in study [8] was also validated (sensitivity of 94.36% and specificity of 98.17%), similar to the significant similarity with the MMSE ($p = 0.012$) and the Clock Drawing Test ($p = 0.050$). Moreover, the discriminant accuracy, as part of reliability, was shown to be sufficient (0.95). Significantly positive correlations and excellent agreement were found between a questionnaire that was not further defined and the results from the technology [1].

Ultimately, the findings of these studies were that ADL differ between PwD and healthy controls. The day-to-day pattern of activity for the PwD was more variable than of the healthy controls ($P \leq .008$) [2], and in other words, the heterogeneity in ADL performance was higher for PwD in comparison to healthy people [8]. Moreover, a significant difference was found in the duration times of sleeping, getting ready for bed, watching TV, toileting, cooking, and seating activities [8]. The number of outings per month were significantly lower for PwD ($P = < 0.001$), and a significantly shorter sleep time ($P = 0.05$) was also observed [1]. Finally, PwD took longer to execute activities, and they initiated and performed fewer activities than the healthy controls [5].

Agitation

Agitation was purposely monitored in three studies [3,6,10]. The actual behaviours to which the researchers attributed agitation differed. Motor activity [3,6] and motor activity, heart rate, decibel level, anger and fear based on pitch, and anger and fear based on speech or words spoken [10] were used to calculate agitation. Two technologies were mounted only on the non-dominant wrist [6] or dominant wrist [10], while the BSN consisted of three nodes namely at the dominant wrist, waist, and opposite leg [3].

With respect to validity, the BSN scores indicated it to be a valid measure. The researchers found reasonable construct validity and acceptable convergent validity for the morning measures. A correlation was found between the morning measures of the BSN with CMAI, and ABS (aggressive behaviour scale). The wrist sensor was the most sensitive in

detecting agitation [3]. Wrist movements positively correlated with MMSE scores (p = < 0.001) [6], however, this was not a result from the BSN network [3]. NPI test scores also correlated with scores from wrist movements (p = < 0.001) [6]. In the pilot study, no significant results were found, because the observer notes did not agree with the findings of the technology [10]. None of the studies reported information about reliability.

The results of these three studies indicate that agitation is monitorable by technology. Lower levels of activity for PwD with apathy from 9:00 to 12:00 and from 18:00 to 21:00 were observed comparison to PwD without apathy [6]. Another finding was that PwD with aberrant motor behaviour showed significantly more motor activity between 9:00 and 12:00 and 21:00 to 24:00. However, no strong association was found between agitation and motor activity. The results from the BSN were that agitated behaviour in the morning was positively correlated with CMAI scores and ABS scores. The higher the CMAI or ABS scores, the higher the agitation scores that were detected [3]. The results from Study [3] and Study [6] are difficult to compare, though both reported significant differences in agitated behaviour in the morning. All three studies for agitation [3,6,10] concluded that limb movements can identify agitated behaviours.

Walking behaviours

Walking behaviours are analysed by stride length, stride time, cadence, velocity, step length asymmetry, and step time asymmetry [11] which are comparable to the parameters of stride, stance, and swing [4] and walking speed [2]. Participants were monitored in their own living environments [2,11], or were instructed to walk along a 40 meter line [4]. According to the researchers of the experimental study, their walking-based technology was able to serve as an assistant indicator for the early diagnosis of AD. The feet- and waist-mounted sensors were equipped with three accelerometers making a detailed analysis of walking and balance abilities possible [4]. It was striking, however, that the study reports of these technologies made no reference to validity or reliability levels.

The reports did, however, showed significant differences in the walking behaviours of PwD and HC. Nine of the 16 gait parameters showed significant differences (p = < 0.05) in the single-task walking test [4]. For example, they found slower walking times, and a higher variance in the stance and swing period of PwD compared to HC. Moreover, all 16 parameters demonstrated significant differences in the dual-task walking test, which requires

higher cognitive performances. Eight of the parameters even had a p-value smaller than 0.001. Balance tests in medial-lateral direction revealed significant shorter balance times for AD patients in a right foot tandem stand with eyes closed and stand on right foot activities. Moreover, the coefficient of variation in the median walking speed was in Study [2] was twice as high in people with first phase dementia as compared to the healthy control subjects. Both Study [2] and Study [11] reported greater variability in walking speed and step time in PwD. Furthermore, PwD were at risk of regularly falling if their step time variability, step length variability, and cadence variability increased [11]. However, the latter results were not significant but still these results are in line with Study [2] and Study [4] as both reported that the walking features of PwD and people without dementia differed.

Sensations

The last category does not imply behaviour but emotions. Two studies were focused on sensations; pain [9] and stress [7], respectively. Stress was measured on the basis of skin conductance. Stress causes an increase in skin conductance because stress is accompanied by a physiological response [7]. However, the utility of the wristband could only be determined if the thresholds per stress level were precisely defined, but fluctuating thresholds resulted in performance changes in precision, recall, and accuracy. The validity and reliability of the wristband has, therefore, not yet been assessed.

The technology focused upon the assessment of pain was a face recognition technology [9]. A pain level was determined by facial expressions namely brow lowering, cheek raising, tightening of eyelids, wrinkling of nose, raising of upper lip, pulling at corner lip, horizontal mouth stretch, parting lips, and closing eyes. In addition to facial recognition, the app is a platform that enables care workers to assess pain on the basis of five additional domains, namely voice, movements, behaviours, activities, and body. This additional information was retrieved through questionnaires consisting of 42 items in total. Care workers are asked to rank body language, which is denoted as fidgeting, rocking, guarding part of the body, or withdrawn, as being absent, mild, moderate, or severe. The magnitude of pain was then measured by obtaining a cumulative score across all the items. The scores of the facial recognition and the observer scores had a Pearson's correlation coefficient agreement of 0.882, which indicates a very strong and positive relationship. Moreover, the discriminant validity between the three aged care homes and inter-rater reliability was moderate to good. Thus, these results indicate that the facial recognition feature of the app could be a valid and reliable measure of pain itself.

RQ 3: How are the data from these technologies operationalised?

All the technologies provide raw data that need to be transformed into finite information. This process consisted of machine learning algorithms for the technologies involved in the walking behaviours [2,4,11]. Three steps were automatically executed to calculate ten gait parameters [2], while another study reported that a validated methodology computed six parameters of gait [11]. The technologies designed to detect agitation also use algorithms to transform their raw data [3,6]. The first steps extracted the clinically relevant information from raw motion data with the use of signal processing algorithms [3]. Thereafter input scores for the Teager energy function test were calculated. The Teager energy function test was then used as a measure of the aggregate energy of the movements.

In comparison with the extensive explanation supplied by Study [3], Study [6] only reported that their process consisted of an analysis of movements from specific algorithms. Moreover, in the pilot study of a multimodal wristband it turned out that the chosen measurements were not suitable [10]. An IBM Blue mix Tone analyser was used to detect emotions from captured speech, but without providing further explanation the researchers found it did not suit for their application. The authors have chosen not to report the statistical analysis in their paper. There were other technologies for which the transformation processes were not extensively reported, except for the information that they work with algorithms[1,7]. The pain detecting technology uses deep learning algorithms to automatically ensure objectivity as it reduces proxy rating errors [9].

Conversely, the transformation methods of the wireless sensor network [8] and EMS [5] were extensively reported. The former made use of an algorithm starting with a classifier that was applied to detect and recognise ADL from the sorted ambient data after which the cumulative sum of the executed activities could be calculated. A Pointcare Plot technique was used to distinguish the variability of the ADL performance and classification. Similarly, the EMS also relied on existing models, namely two of the Naïve-Bayes models [5]. The system itself firstly extracted fine- to coarse performances that served as input features for the Naïve-Bayes models to classify the performances into autonomy parameters.

RQ 4: What are the advantages and disadvantages of different technologies?

Each technology has its own strengths and weaknesses, however, some elements were commonly observed among the eleven technologies. A strength of the technologies is that

they all work automatically without the intervention of human energy, except for the ePat [9]. One of the disadvantages of the technologies is that seven of the technologies have not yet been tested for reliability [1-4,6,10,11] (Table 6). A technology must possess a sufficient level of reliability before it will be purposely recommended by care workers.

In addition, with regard to the appearance of the wearable devices, opinions were divided regarding their unobtrusiveness. In one study, the participants opted out of the study because they found their wearable devices annoying [11], while other devices appeared to be less obtrusive given that the participants accepted and tolerated the equipment [3,6]. However, the researchers in Study [4] and Study [11] reported that their system was unobtrusive, but the participants were required to wear several pieces of equipment. The level of unobtrusiveness may also be an explanation for the differences in the duration of the monitoring. The range for the wearable devices was between 8 hours to 10 days, while the duration of the wireless systems ranged between 20 days and 26 weeks. A possible explanation for this fact may be the unobtrusive characters of the wearable devices.

More can be said about the unobtrusiveness and feasibility of the technologies. Some devices needed to be charged during the night, requiring care workers or relatives to help mount and unmount the technology [3,4,7], although the researchers reported that it was easy to connect and remove the BSN [3]. In contrast, the difficulty level of the facial recognition app was high, which meant that care workers had to be instructed in how to cope with the app [9]. As all the wearable devices were equipped with accelerometers in different forms, these appeared to work well.

With regard to the wireless and Kinect technology, these have been designed with one major drawback. These technologies can only be a reliable measurement in one-person households [1,2,5,8,11]. This can be solved by providing residents with tags, but then the technology is no longer unobtrusive [2]. Notably, the researchers who did use RFID tags reported that these were somewhat cumbersome [11]. Technology that cannot differentiate between residents and visitors will not provide reliable data. Therefore, facial recognition software is suggested to solve this problem [11].

A strength of some of the studies covering ADL is that they include a substantial number of normal daily living activities [5,8]. However, even simplistic sensory systems can already detect significant differences between PwD and HC and are low costs as well [1]. It should also be noted that technologies that are installed in people's homes need to be installed and configured through human effort before they are useful. Subsequently, devices loitering around in someone's home may feel distracting. Although some researchers already take this

into account by placing the sensor boxes in such a way that they do not disturb the field of vision [8], invisible technologies will not create the feeling of 'being watched'. The researchers of one of the ADL recognition technologies reported that the participants' stress levels may have been changed by the feeling of being watched and that their performances could be influenced by this [5].

Another setback of the technologies is the number of errors that have arisen in their use. The wristband with the skin conductance meter resulted in errors when the band was accidentally not fully attached to the skin [6]. Moreover, the Kinect technology appears to produce many errors [11]. Due to a Kinect skeletal tracking failure, more than half of the recordings needed to be deleted. This happened when participants walked away from the sensor. The system also demonstrated problems when participants walked very close to a wall. In addition to these technical failures, environmental noises resulted in the voice analysis being invalid in the pilot study [10]. The skin conductance wristband possesses another major setback, which is that skin conductance differs per person causing it to be difficult to determine thresholds. Skin conductance can also change due to changes in environment temperature and by physical activity [6].

Last but not least, it is striking that none of the studies involved measures or discussions about privacy. One might argue that sensors placed in homes may change the resident's sense of privacy. The same holds true for information about stress and pain because this is sensitive information. These concerns are not directly a disadvantage of the technologies, but out of respect for the users of these devices this issue of privacy does need to be investigated. Consequently, these aspects are a major disadvantage of the studies.

Table 6

Advantages and disadvantages of the different technologies, established by the data extraction rules

Study number	Authors	Comparison scales	Validity	Reliability	Automatized	Unobtrusiveness	Feasibility
3	Bankole	MMSE, CMAI, ABS	+	N/A	+	+	+
4	Hsu	None	N/A	N/A	+	N/A	N/A
6	Valembois	MMSE, NPI	+	N/A	+	+	+
7	Kikhia	Observer notes	-	-	+	N/A	N/A
10	Nesbitt	CMAI, observer notes	-	N/A	+	N/A	N/A
1	Suzuki	MMSE, questionnaire*	+	N/A	+	N/A	+
2	Hayes	MMSE, CDR	N/A	N/A	+	+	-
8	Urwyler	MMSE	+	+	+	+	-
5	König	MMSE, NPI, observer notes	+	+	+	N/A	+
11	Dolatabadi	NPI	N/A	N/A	+	+	+
9	Atee	MMSE, observer notes	+	+	-	N/A	N/A

Notes: Study numbers [3,4,6,7,10] used wearable devices, study numbers [1,2,8] used wireless network systems, study numbers [5,11] used Kinect sensors, study number [9] used a mobile application. A + (plus) = a positive finding. A – (minus) = a negative finding. * = no more information about the questionnaire was given. N/A = not available. MMSE = Mini Mental State Examination. CMAI = Cohen-Mansfield Agitation Inventory. ABS = Aggressive Behavior Scale. NPI = Narcissistic Personality Inventory. CDR = Clinical Dementia Rating.

Discussion

Conclusion

The aim of this scoping review was to identify the current literature on the technologies that monitor behavioural and emotional symptoms in PwD. The state of the art in the development of monitoring technologies is now clearer. The type of technologies that are currently been designed are wearable devices, wireless sensor systems, Kinect sensor systems, and a mobile app. The behaviours and emotions that are monitored are divided into ADL, agitation, walking behaviours, and sensations. However, only the technologies utilised for ADL and agitation have been validated. Most of the data are operationalised with the use of machine learning algorithms. The major advantage of the technologies is that they automatically detect and transmit data, while the disadvantages mainly lie in a lack of validity, reliability and issues of privacy.

Discussion

The investigation conducted of the currently used technologies shows that the technologies concerning walking behaviours have not been tested for reliability and validity, while the other types of behaviours were tested in at least one study. This shortcoming may be for several reasons. It may be that the research conducted upon this topic is very new, causing the researchers to focus on reliability and validity at a later stage. It may also be that walking behaviours are considered to be an unimportant factor in detecting disease progression. When examining the publication years of the studies the first reason cannot be confirmed. The studies from 2008, 2014, and 2019 might have shown progress in this area but this is not the case. However, it is not mandatory for researchers to report information on validity and reliability. The second argumentation can be rejected as many prior studies have noted the importance of analysing walking performances of PwD.

The performance of a routinely executed behaviour such as walking is correlated with cognitive function (Tabbarah, Crimmins, & Seeman, 2002). Moreover, the time it takes to walk 30 metres is an independently predictor of the onset time of persistent cognitive decline (Marquis et al., 2002). It has even be proven that walking exercises have a beneficial effect on cognitive functions in PwD (Kemoun et al., 2010). In view of the promising findings, it seems valuable to continue concentrating the design of new technologies upon walking behaviours. However, to develop a technology that detects changes in walking performance, additional studies are needed that execute validity and reliability tests. In addition, the extent of

reliability testing for all behavioural and emotional symptom monitoring devices can be improved, since only four of the eleven studies included reliability tests of which one was insufficient reliable. So, technologies need to be tested multiple times and with multiple participant groups to be able to completely test its reliability. Then, and only then, global support for the technology will increase.

While the literature has taken its first steps into the new field of technology that automatically detect behaviours, the development of technology that detects emotions appears to be lagging behind. Only two of the eleven included technologies were focussed on emotions, namely stress and pain. In addition to these two emotions, agitation can also be seen as an emotional symptom because people become aroused and restless (Cohen-Mansfield & Billig, 1986). However, due to the fact that agitation is expressed outwardly by a person, it has been classified as a behaviour. Activities of daily living are also expressed outwardly, while cognitive abilities are required to initiate and execute activities In contrast, pain and stress are classified as emotions, because these predominantly causes discomfort inside the body. This may be the reason that emotions are more difficult for technologies to detect.

Nonetheless, research should still be conducted to find solutions for monitoring more sensations, because a prior study shows that PwD experience diminished emotional responsiveness, impaired emotional control and apathy, which is a decrease in interest and enthusiasm (Balsis, Carpenter, & Storandt, 2005). The same study found that these changes begin at an early stage of the disease, in which consciousness is not affected. An altered emotional well-being may be frustrating for PwD and they may try to hide these symptoms in the presence of others. Therefore, it would be valuable to extend the development of technologies that detect emotional changes in PwD continuously .

The last finding that needs to be discussed is the lack of privacy evaluations. None of the studies included privacy evaluations. It seems obvious that the users of the technologies would have an altered sense of privacy, or at least an opinion about their privacy. Other researchers also found that privacy concerns are a major unsolved topic around wearable and wireless monitoring systems (Li, Lou, & Ren, 2010; Mukhopadhyay, 2014). One of the aspects that may hinder public acceptance of such technologies is the limitation of authorized users that have access to patient-related data (Li et al., 2010). In addition, questions regarding to whom the data should be disclosed and who will be responsible for the safe storage of the data need to be answered very clearly in order to protect the privacy of users (Meingast,

Roosta, & Sastry, 2006). It should also be noted that data which are transmitted by wireless systems are vulnerable to online risks such as hacking.

Limitations and strengths

With regards to the process of executing this review, a number of limitations and strengths were identified. Firstly, limited appropriate studies were found in the Scopus database seeing that more databases would have shown more studies that met the in- and exclusion criteria. Thus, not all relevant studies about dementia monitoring technologies may have been selected. This automatically means that an extensive literature review in more databases may result in discovering more technologies.

In addition, the search process was executed by only one reviewer. It might be that a replication of this literature review by another reviewer would result in other points of attention, due to differing personal opinions and frames of reference. It cannot be overlooked that different researchers use different search terms and in- and exclusion criteria as well. However, a strength of the current inclusion criteria was the unrestricted minimum number of participants in the studies. As this field of research is new, a restriction of at least 50 participants would have resulted in a literature review of three studies, rather than eleven.

Another decision that was made was not to extensively assess the quality of the potential studies. This was thought to be beyond the abilities of a junior researchers. However, studies that passed the title and abstract requirements but turned out to be difficult to read and understand were not further assessed for in- and exclusion criteria but immediately avoided. Furthermore, a strength of the studies was that they all used one or more clinical tests to classify their participants as dementia patients or control subjects. A major consideration after executing this literature review is that the researchers aiming to prove the utility of their technologies, but in so they omitted considerations of ethicality. A lack of user-centred designs was already proven as a major setback in the support for new technologies (Neubauer et al., 2018).

To develop a product that receives global support it needs to find agreement in the degree of privacy invasion and user friendliness. Therefore, it seems wisely to involve multiple stakeholders such as early, middle, and late stage dementia patients and caregivers into the design process. The researchers can now adapt their device accordingly to the norms and wishes of the end-users. Moreover, as a monitoring technology is going to be tested opinions of the users need to be collected to either adjust the technology or to prove its standards. At the time that monitoring devices act sufficiently according to the degree of

privacy invasion and user friendliness, next to requirements such as validity, reliability and feasibility concerns, many PwD, caregivers, and other stakeholders will benefit from these technologies.

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