

## **Digital Technologies for the Assessment of Cognition: A Clinical Review**

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### **Abstract:**

Dementia is the most widespread neurodegenerative disorder globally, and is associated with an immense societal and personal cost. With dementia prevalence projected to triple worldwide by 2050, there is an urgent need to increase the efficacy of dementia prevention, treatment and care. Rapid advancements in digital technology is starting to provide new opportunities to alleviate some of the challenges faced by dementia clinicians and researchers. This clinical review aims to summarise the current evidence for the use of pervasive digital technologies to monitor and support cognition in pre-clinical, prodromal and demented populations. Generally, the digital technologies provided valid measures of users' cognitive function. However, most of the systems are still in the initial development stages, with limited data on acceptability in patients. Although the use of digital technology to monitor and support cognitive domains affected by dementia is a promising area of development, additional research validating the efficacy, utility and cost-effectiveness of these systems in patient populations is needed.

## **Introduction:**

In 2015, Alzheimer's Disease International reported that an estimated 46.8 million people were living with dementia worldwide, with an associated cost of US\$818 billion<sup>1</sup>. With the percentage of the world population aged over-60 predicted to double by 2050<sup>1</sup>, the societal, economic and personal burden of this "dementia epidemic"<sup>2</sup> is a major concern for the sustainability of healthcare<sup>3</sup>. It has been argued that addressing preventable risk factors for dementia, such as sedentary lifestyle and poor diet, could reduce the disease burden<sup>3</sup>. To achieve this, we must understand which risk factors to target, and whether a critical intervention period exists.

Omnipresent digital technologies, such as smartwatches and smartphones, could help address these two issues, through their ability to obtain a wealth of ecologically valid, longitudinal information on health, behaviour and cognitive function. This rich feedback provides new opportunities to identify potentially modifiable risk factors, detect early changes in behaviour indicative of disease and track disease trajectories over time<sup>4</sup>.

As well as monitoring health and cognition, digital technologies that provide adaptive assistance are now emerging due to advances in machine learning. The application of domotics - the integration of technology into residential structures<sup>5</sup> – to dementia care has resulted in the development of adaptive "smart homes" to assist patients with Activities of Daily Living (ADLs) affected by their cognitive deficits<sup>6</sup>. With the majority of dementia care costs falling on unpaid carers and long-term institutional social care<sup>7</sup>, technological developments promoting patient independence and quality of life, will be crucial to reducing the growing burden of neurodegenerative diseases.

Beyond providing assistance, digital technology is being explored as a potential method of non-pharmacological intervention. Cognitive training smartphone applications, which aim to strengthen various cognitive domains<sup>8</sup> (defined by the National Institute of Health as Attention, Perception, Declarative Memory, Language, Cognitive Control and Working Memory<sup>9</sup>), are particularly prevalent. There is already evidence that 'structured programs of cognitively demanding computer tasks' can

be beneficial for healthy brain ageing<sup>10</sup>. The adaption of these programs into downloadable smartphone applications addresses several former limitations including: integration into daily life, implementation burden, and distribution scope<sup>11</sup>.

This review aimed to provide a summary of current developments in digital technologies for cognitive monitoring, assistance and training in elderly demented, prodromal and pre-clinical populations. We focused our search on three technologies based on their immediate relevance to cognition, dementia and healthcare: mobile (smartphone and tablet) applications, wearable technology and smart home systems.

## **Methods**

We searched PubMed, Science Direct and Google Scholar records (last search 25/10/2017) using the terms: 'mobile technology' or 'wearable technology' or 'smartphone' or 'smartwatch' or 'smarthome' or 'domotics' and 'dementia' or 'cognition' or 'elderly' or 'Alzheimer's' or 'health'. Articles in English were screened, and studies selected that evaluated digital technologies to monitor or assist cognitive function in older adults. We included technologies that deduced cognitive function through ADL performance. Articles piloting relevant technology in younger adults were also included when intent to apply the technology to older populations at risk of, or living with, dementia was demonstrated. Additional studies, referenced by articles identified in the original search, were also included. Due to the heterogeneity of digital technology and outcomes reviewed, a comprehensive systematic review was beyond the scope of this paper.

## **Presentation**

Our review identified 24 articles detailing digital technologies with capacity to analyse cognitive function in older adults at various stages of a dementing disease; see the technology index (Table 1).

### ***Mobile applications***

Seven identified articles presented cognitive-focused smartphone/tablet apps. The apps' objectives could be generally divided into three categories: cognitive monitoring, assistance and training.

#### *Cognitive Monitoring:*

Three applications were designed to monitor cognitive function in older adults. iVitality<sup>12</sup> and Color-Shape Test (CST)<sup>13</sup> aim to provide reliable means to assess cognition in 'at-risk' populations for dementia; DelApp<sup>14</sup> focuses on identifying delirium in hospital inpatients.

iVitality employs five digitally adapted versions of standard cognitive tests (Stroop, Reaction Time, Trail Making, N-Back and Memory-Word tests)<sup>12</sup>. The tasks were piloted on 151 individuals with familial risk of dementia (mean age 57) over six months<sup>12</sup>, with moderate correlation for digital Trail Making and Stroop against their lab-based counterparts (correlation coefficients range 0.4-0.6) and adherence ranging from 48% to 67%. The developers concluded that smartphone-based cognitive testing is feasible in cognitively normal individuals aged 50+ years, with acceptable levels of correlation with gold standard, lab-based testing<sup>12</sup>.

CST is a smartphone-optimised webpage developed to measure cognitive processing speed in the elderly<sup>13</sup>, through participants' learning and recalling shape colours. In a feasibility study of 57 cognitively healthy older adults CST performance correlated with performance on standard measures of global cognition (MMSE), processing speed and attention (Digit Span and Trail Making tests), but not tests of executive function (verbal fluency) or episodic memory (Logical Memory Test)<sup>13</sup>. As only 18 participants had prior possession of a smartphone, the author's concluded the task's usability in older adults was not dictated by smartphone familiarity.

DelApp is a computerised version of the Edinburgh Delirium Test Box (EDTB); an assessment of visual sustained attention in general hospital inpatients<sup>14</sup>. No statistical difference was found between performance on the DelApp and the standard EDTB in 20 elderly cognitively healthy inpatients. DelApp also reliably differentiated patients with delirium from dementia patients (despite

comparable cognitive performances) and from those with no cognitive impairment in 156 elderly inpatients (AUC = 0.96 with 98% sensitivity and 93% specificity)<sup>14</sup>. The conclusion was that DelApp provides an accessible and reliable means of monitoring delirium emergence in inpatient populations.

#### *Cognitive Assistance:*

Technology Adoption and Usage Tool (TAUT)<sup>15</sup>, was designed to provide cognitive assistance for individuals with episodic memory deficits through an adaptive ADL reminder system. By assimilating information from user inputs and context-aware sensors, the app adapts reminder delivery to improve integration with the user's lifestyle over time. TAUT is currently is being tested in an elderly, cognitively impaired population<sup>16</sup>, following a pilot in healthy younger adults where 73% of reminders were acknowledged within 12.38 seconds<sup>15</sup>.

#### *Cognitive Training:*

Four apps were designed as primary and secondary dementia prevention methods with varied cognitive targets. Two apps, SMART and Fit Brains<sup>17</sup>, utilise multi-domain programmes of gamified cognitive tasks to improve cognitive reserve in preclinical older adults. SMART specifically targeted attention and memory (working and declarative), while Fit Brains generally covered most of the NIH cognitive domains<sup>17</sup>. In a randomised control trial, the efficacy of the apps for improving working and declarative memory in 53 older adults (mean age 59 years) with subjective memory complaints was investigated comparatively over 8 weeks<sup>17</sup>. Statistically significant improvements in overall and auditory-verbal working memory scores on the Memory Diagnostic System (MDS, a computerized neuropsychological battery<sup>18</sup>) were demonstrated for SMART, but not Fit Brains. The authors concluded that the greater focus of the SMART programme's tasks led to the working memory improvements on the MDS. However, this did not translate to participants' self-reported memory contentment, which only improved post-test in the Fit Brains group<sup>17</sup>.

Two additional cognitive training apps are currently in design. The modified Attention Training Application (ATA)<sup>19</sup> implements an adaptive working memory and attention (dual-n-back) task over two weeks to reduce executive deficits in people with mild cognitive impairment (MCI). The task was piloted on twelve MCI patients and healthy older adults (mean age 79 years), who on average rated the ATA as 60% interesting and 72.5% easy to use<sup>19</sup>. Suggested modifications are being implemented for future feasibility testing.

Healthebrain<sup>8</sup> employs a three week Square-Stepping Exercise (SSE) to improve visuospatial memory in preclinical and MCI older adults. The user learns and reproduces patterns displayed on a smartphone screen by walking, holding the device parallel to the floor<sup>8</sup>. Non-computerised SSE has been observed to improve global cognitive functioning, especially attention and cognitive control, in older adults<sup>20</sup>. On piloting the app with 19 healthy or MCI older adults (mean age 68 years), 60% of the participants reported the app easy to use, or comparable to the lab-based SSE task<sup>8</sup>. Future work is needed to establish the validity of an app-based SSE program as a cognitive intervention.

### ***Wearables***

Ten studies identified reported wearable technologies (smartwatches, accelerometers, cameras and glasses) for elderly preclinical and demented populations, with objectives that could be divided into cognitive monitoring and assistance.

#### ***Cognitive Monitoring:***

Smartwatches: Four articles presented smartwatches that assess physical and, by proxy cognitive, function in dementia patients. WanderRep<sup>21</sup>, is a smartwatch-based reporting tool for caregivers of wandering persons with dementia. The smartwatches' ability to record time, location, temperature and activity level is used to create a personalised profile of wandering risk. By modelling patient behaviour, irregular and dangerous wandering can be detected, and caregivers alerted<sup>21</sup>. The authors piloted the smartwatch with one care home based dementia patient, and five professional

caregivers who determined potentially dangerous wandering events. The system reported high sensitivity and specificity to detect dangerous events (78% and 89% respectively) and thus supporting their use in supporting independent living<sup>21</sup>.

Three identified systems (Max<sup>22</sup>, u-Healthcare<sup>23</sup>, Basis B1<sup>24</sup>) use smartwatch-derived measures to create activity profiles of dementia patients. Both Max and u-Healthcare rely on location and step data to infer activity; Max employs a Bluetooth sensor system to obtain room-specific data, while u-Healthcare utilises GPS, accelerometer and ambient light sensors to profile physical activity inside and outside the home. Max was piloted in the homes of thirteen healthy controls from the Dementia Care Ecosystem<sup>25</sup> over 39 months<sup>22</sup>. Reported room detection accuracy was 91%, and distinct user behaviour patterns could be detected. u-Healthcare was trialled in 8 participants with average step detection accuracy of 94.7% reported<sup>23</sup>.

Basis B1 monitors dementia patients' activities using broader biological measures (optical blood flow, body temperature and galvanic skin response) captured by a smartwatch, combined with medical history<sup>24</sup>. It was piloted with one dementia patient alongside their existing home-based care and was reported not to cause discomfort or anxiety, and provided the caregiver with new information on the patient's night disturbances, sleep and physical activity<sup>24</sup>. These results suggest that smartwatch monitoring systems could be complementary tools for existing care practices by monitoring cognitive health and behaviour when caregivers are unavailable, and patient self-report is unreliable<sup>24</sup>.

Smartwatch technology has also been developed for preclinical populations. The Wrist Wearable Unit (WWU)<sup>26</sup> monitors home-based physical activity levels of preclinical older adults longitudinally using measures of step count, acceleration, and heart rate. Routine user activity, and subsequent deviations, are reported to healthcare professionals via an online platform. WWU was piloted in groups of two to twenty healthy adults<sup>26</sup>. WWU-derived activity levels correlated well with users' subjectively reported activity, WWU-calculated heart rate fell within  $\pm 4$ bpm of pulse oximeter

measures, and device worn/unworn status was correctly identified to one minute accuracy<sup>26</sup>. The authors concluded that WWU could help to reliably determine preclinical function, from which changes indicative of physical and cognitive decline could be ascertained.

Accelerometers: Accelerometers, portable electro-mechanical sensors, offer a more established and lower cost activity monitor than smartwatches. One study used accelerometer data to monitor older adults' physical activity, intending to infer cognitive status<sup>27</sup>. A waist-worn triaxial-accelerometer was used by 274 community-dwelling older adults over 22 months. Light physical activity (measured by the accelerometer and defined using established cut-offs<sup>28</sup>) was independently associated with lower scores (i.e. better cognitive function) on the AD8 - an eight-item informant interview probing memory, orientation, judgment, and ADLs<sup>29</sup> at follow-up<sup>27</sup>. The study suggested that promotion of higher levels of objectively measured light physical activity could help protect cognitive function in older adults.

Wearable Cameras: One study utilised a custom-made wearable camera system, worn by caregivers, to monitor patients' dementia-related behaviour<sup>30</sup>. The system was piloted with 18 dementia patients and their caregivers over two, seven-day periods or for one three to five day period. 341 hours of usable video was collected, containing 248 salient events (dementia-related behaviour or caregiving interactions<sup>30</sup>). Further development may lead to this technology being used to provide validation of caregiver observations, and provide accessible, unbiased monitoring of changes in patients' behaviour, cognition and needs over time<sup>30</sup>.

### *Cognitive Assistance*

Smartwatch: One study investigated commercially available smartwatch technology to provide ADL assistance for dementia patients<sup>31</sup>; implementing smartwatch apps, and a paired smartphone, to assist scheduling, navigation, orientation to time and communication, as well as monitor activity levels. The system was tested by five memory clinic patients and their spouses in a controlled lab setting. Initial feedback suggested only the scheduling, orientation and communication functions



were usable (90-100% success rate completing tasks using these functionalities, compared to 0% on the navigation and emergency help tasks)<sup>31</sup>. Results from a follow-up home pilot are pending.

Wearable Camera: SenseCam<sup>32</sup> is a wearable camera system supporting autobiographical memory consolidation and retrieval in cognitively impaired people. SenseCam captures pictures every 30 seconds, or in response to specific triggers e.g. movement, which the patient subsequently reviews<sup>32</sup>. During a two week testing phase, the MCI patients' proportion of events correctly recalled increased significantly from 38% at baseline (no review) to 68% at day 13; while a diary review method showed no significant change in the patient's recall at day thirteen (30%)<sup>32</sup>. This recall difference for events reviewed using SenseCam, a diary or no review was sustained at six months' follow-up. The patient also reported an increase in self-esteem and confidence.

Smart Glasses: One article presented a head mounted display system to assist mild-to-moderate dementia patients with navigation inside and outside the home<sup>33</sup>; consisting of a pair of smart glasses implanted LED lights and various sensors (including accelerometers and a GPS tracker), which communicate with a remote android unit via a Bluetooth headset. Caregivers can use the remote unit to monitor the patient's location and send navigational cues through the glasses LED's. Acceptability of visual navigational cues was demonstrated in feasibility testing in a group of dementia patients, with cue usability significantly influenced by LED positioning and dementia severity<sup>33</sup>.

### ***Smart homes***

Extensive research exists into applying smart home technology to dementia populations, focusing on providing daily assistance. While not designed to directly monitor cognition, by observing changes in patients' ADLs, we here report seven smart home systems which have potential to infer and monitor cognitive function.

### *Cognitive Monitoring:*

Smart home monitoring and assistance typically uses a 3-stage iterative process. Technologies in the infrastructure of the building - for example magnetic contact sensors, passive infrared motion sensors, and pressure mats<sup>34</sup> - monitor the environment. Machine learning principles then conceptualise the data into patterns of behaviour, and subsequent deviations<sup>35 36</sup>. Finally, a decision-maker system reacts to behavioural deviations and provides real time feedback to patients' and caregivers<sup>34</sup>. One study found acceptance of smart home monitoring and alert technology by patients and their families was predicated on perceived enhancements to the safety, and independence, of the patient, and to delay institutionalisation.<sup>37</sup>

Three identified studies assessed the accuracy of smart homes to determine participant's performance while completing ADL. The M2M/IoT platform smart home showed ADL detection accuracy to be 80-100% for most activities, including wandering detection and forgetting to take a shower<sup>38</sup>. The DemaWare2 system reported an average of 82% precision for recognising activities performed in a lab environment and 75% for activities performed in a residential smart home<sup>35</sup>. The third, found a significant correlation ( $r=0.54$ ) between the scores of ADL performance assigned by clinicians observing patient behaviour, and the performance scores assigned by the smart home<sup>36</sup>. However, for all, the smart homes accuracy for determining the user's performances varied depending on the type of activity being assessed; all three studies found smart home predictions of watching television, including remembering to turn off the TV, were less accurate than other ADLs. One explanation given was that quicker activities, involving fewer sensor interactions, were harder for the smart home to accurately identify, so subsequent deviations were less likely to be detected<sup>36</sup>. Sensor type may also make a difference e.g. detection of "forgetting to turn off the TV" was reliant on the sound exceeding the sensors threshold<sup>38</sup>.

A collection of studies from one Lab has assessed whether by monitoring a number of ADL, a smart home could detect cognitive function and decline. The ORCATECH group collected continuous, daily

data from 480 homes since 2007, using an unobtrusive activity monitoring smart home (comprising motion, contact and pressure sensors, computer and phone monitoring, medication trackers and wireless scales)<sup>39</sup>. One study reported no differences in daily recorded computer activity (based on mouse movements) at baseline between groups of cognitively healthy compared to MCI participants; however, at follow-up two and three years later, a significant decrease in number of days with computer use, mean daily use and an increase in day-to-day variability was found in the MCI group compared to the cognitively healthy participants<sup>40</sup>. The authors concluded that computer usage is likely to be sensitive to cognitive change due to its reliance on multiple cognitive domains. The same investigators monitored medication adherence using a device with sensors built into the medication box signalling open and close events, demonstrating that the participants who performed worse on the Alzheimer's Disease Assessment Scale Cognitive Subtest (ADAS-cog) had significantly poorer medication adherence than the better performing group<sup>41</sup>.

The capability of two smart home systems to discriminate cognitive states and dementia status has also been examined. DemaWare2 system<sup>35</sup> monitored data from 27 Alzheimer's disease, 38 MCI and 33 cognitively healthy participants as they performed ADLs in a lab-based smart home. For the ADLs "making a phone call" and "paying a bank bill remotely", the system could distinguish between the three participant groups with up to 84% accuracy<sup>35</sup>. Similarly, the second study evaluated the ability of a machine learning method to classify the cognitive health status of 263 participants (196 cognitively healthy, 51 MCI and 16 dementia patients) from 8 ADL performed in a lab-based smart home<sup>36</sup>. Reasonable accuracy in differentiating between cognitively healthy and dementia participants was reported when combining data from all 8 ADLs, and on some individual ADL (sweeping, cooking and dressing), but not for differentiating between cognitively healthy and MCI. By including only ADLs that demonstrated good prediction accuracy in isolation, the classification performance of the combinatorial model was improved<sup>36</sup>. These studies demonstrate that, while still in pilot stages, monitoring ADL performance by smart homes is feasible and can identify cognitive decline over time and infer cognitive states and dementia status.

## **Discussion**

Through this review we attempted to highlight the breadth of digital technology currently available for the assessment of cognitive function in elderly demented and pre-clinical populations. We identified technologies that allow direct monitoring of cognition (e.g. smartphone app) and those that monitor broader indices of activity and function that could deduce cognitive ability. This is a rapidly developing area, with the number of dementia-focused digital technologies doubling approximately every five years<sup>4</sup>. The timely adoption of such technology in clinical practice is a challenge that requires effective communication between developers and clinicians about the availability of such solutions<sup>4</sup>. Overcoming this barrier could provide some of the most promising opportunities to reduce the burden of dementia.

The main value currently available digital technology can offer, in terms of cognitive monitoring, is the capacity to provide more ecologically-valid, high-granularity data. This type of data could be crucial in the development of much needed pharmacological dementia treatments. Despite considerable investment, no disease modifying treatments are currently available, with several high-profile failures<sup>3</sup>, which may have been due to testing compounds too late in the disease process. Longitudinal, high-frequency measurements by digital technologies could detect subtle cognitive changes at-risk populations, allowing targeted interventions early in the illness.

Longitudinal monitoring of behaviour and physical health could also be of immediate benefit clinically. Systems providing information on potentially fluctuating neuro-behavioural symptoms, not displayed at clinic visits, may assist clinicians making earlier diagnoses from fewer visits. This could therefore reduce the time and cost burden for both clinicians and patients. Similarly, technological monitoring will enable clinicians to objectively track behavioural and cognitive changes more closely over time<sup>34</sup>, reducing the need to rely on subjective accounts. Finally, such systems can provide feedback directly to at-risk participants allowing for behavioural interventions where modifiable risk factors are concerned.

For existing dementia patients, the development of increasingly adaptive, assistive systems can help preserve independence levels and quality of life for as long as possible<sup>42</sup>. Maintaining independence is a crucial goal for the sustainability of dementia care, as current population prediction show caregiver-to-patient ratio is expected to reduce dramatically by 2050<sup>4</sup>. Furthermore, the trend of adults moving away from cities into rural areas post retirement poses a significant challenge to healthcare delivery. Therefore the development of systems that provide support and prevent emergency situations<sup>24 34</sup> when carers are unavailable, or allow carers to remotely monitor and assist multiple patients<sup>34</sup>, will be increasingly important in the future<sup>4</sup>.

Despite the potential advantages of deploying digital technology to both dementia research and care, it carries ethical implications. Consent, and capacity, is particularly relevant given the potential security and privacy threats associated with intelligent technology<sup>43</sup>. Patient confidentiality may be violated by an intrusion upon, or revelation of, something private; such violations are considered to include use of video or audio technology<sup>35</sup> and content of feedback given to carers. While data collected should be secure and encrypted to maintain confidentiality, there are inherent security risks when collecting and transferring personal data via a network<sup>43</sup>. Privacy and security are major considerations in user adoption of digital technology, with higher acceptance reported for non-invasive, reliable equipment<sup>40</sup>.

A further ethical concern is socioeconomic barriers that may prevent utilisation of digital technology for healthcare across society<sup>4</sup>. While few of the reviewed studies reported any costs of the technologies implemented, it is unlikely to be trivial. Beyond the initial hardware cost, further hidden costs associated with technology usage, update and protection (for example internet access and insurance policies) may cause a socioeconomic divide. Such finances need to be managed, and with cognitive decline often affecting ADLs such as financial organisation<sup>35 36</sup> the burden associated with introducing smart technology may be considerable and infeasible. Nevertheless, digital monitoring of those with cognitive decline may provide a lower-cost alternative to full-time care<sup>34</sup>.

These arguments highlight the need for research investigating the cost-benefit ratio of technologies and variations between demographic groups.

Although out of this reviews scope, it is worth mentioning there are many new digital technologies on the horizon which could be adopted for dementia care. One such development, broadly referred to as 'bodyNET'<sup>44</sup>, involves a network of sensors and smart devices worn as part of clothing, on the skin, or even implanted into the body. This technology is early development but should allow for a passive data monitoring that can be used alongside the principles of assistive technology<sup>44</sup>. Other technologies are being specifically developed to target dementia-related deficits. One example is PARO<sup>45</sup>: a socially-assistive robot seal pup, which has been shown to increase social interactions between dementia patients in a group therapy session. Another system, BikeAround<sup>46</sup> employs a stationary bike paired with a virtual-reality projection of Google Street View to allow dementia patients to "visit" personally significant locations and, in doing this, tap into their autobiographical memories.

In conclusion, developments in digital technology for the monitoring and assistance of older adults with and without a dementing disease is a rapidly growing area of interest. This technology has the potential to greatly improve the efficiency of dementia drug development, as well as optimise the provision of dementia care in settings of increasing demand. Many of the developments appear promising in their initial pilot stages, however further research is needed to validate the measures and assess long-term outcomes of users.

**Word Count: 3864**

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Table 1. Digital technology index: Summary of studies included in clinical review. Abbreviations: Activities of daily living (ADL), Alzheimer's Disease (AD), Area under the curve (AUC), Clinical Dementia Rating (CDR), Colour-Shape Test (CST), Global positioning system (GPS), Interquartile range (IQR), Light emitting diode (LED), Mild Cognitive Impairment (MCI), Mini-Mental State Examination (MMSE), Receiver operating characteristic (ROC), Smartphone-based brain Anti-Ageing and memory Reinforcement Training (SMART), Standard Deviation (SD), Trail Making Tests (TMT).

Study	Techno logy name	Techno logy type	Cognitiv e target	Develop ment stage	Particip ants	Primary outcome	Result
<b>Smartphone Applications</b>							
Brouillette et al. (2013)	Colour-Shape Test (CST)	Smartphone application	Processing speed	Proof-of-concept	57 healthy older adults. Age: mean 67.18 years (SD $\pm$ 1.02)	Comparison of performance on app with scores on standard assessments of cognitive processing speed and cognitive function.	Scores on CST significantly positively correlated with global cognition (as measured by MMSE), processing speed and attention (as measured by digit span, trail making and digit-symbol test). Test-retest reliability was significant.
Hartin et al. (2014)	Technology Adoption and Usage Tool (TAUT)	Smartphone application	Prospective memory	Proof-of-concept	9 healthy younger adults. Age: median 27 years	Adherence to reminder alerts	73% of reminder alerts were acknowledged (within a mean response time of 12.38 seconds), despite 80% of reminders interrupting the participant during another activity.

							Reminders for all ADL categories available were used.
Hill et al. (2017)	Modified Attention Training Application (ATA)	Tablet application	Attention	Proof-of-concept	12 older adults without moderate-severe cognitive impairment. Age: mean 79 years (SD $\pm$ 4.2)	Feedback on the usability and acceptability of the app for attention training.	On average participants rated the app positively (60% or higher). A preference for challenge, speed and variety was demonstrated. Main limitations included: lack of engagement, technical difficulties and confusion regarding use.
Jongstra et al. (2017)	iVitality	Smartphone application	Working & short-term memory, attention, executive function	Proof-of-concept	151 healthy older adults with parental history of dementia. Age: mean 57.3 years (SD $\pm$ 5.3)	Feasibility and validity of smartphone-based neuropsychological tests to assess various aspects of cognitive function.	The app version of the Stroop and TMT moderately correlated with performance on the conventional test versions. Performance on the app Stroop and TMT reversed alphanumeric tasks improved with repeated testing. Mean adherence to assigned smartphone tests was 60% at 6 months.
Oh et al (2017)	Smartphone-based brain Anti-Ageing and memory Reinforcement Training (SMART) and FitBrains©	Smartphone applications	Attention, working memory and executive function	Validation	53 older adults with subjective memory complaints. Age: mean 59.3 years (SD $\pm$ 5.09)	Subjective and objective improvements in memory (as measured with standard questionnaires) post-app use.	Total and auditory-verbal working memory scores increased significantly in the SMART group compared to both control groups. However, self-reported memory contentment only significantly improved in the FitBrains group.

Shellington et al. (2017)	Healthe Brain	Smartphone application	Visuospatial memory	Proof-of-concept	19 healthy or mildly cognitively impaired older adults. Age: mean 68.3 years (SD ± 5.4)	Feedback on the usability of the app to deliver exercise-based, visuospatial tasks outside the lab.	19/95 contacted participants successfully downloaded the app and completed the survey. 60% of participants found the app easy to use, or similar to previous experiences. 9 participants said they would continue to use the app in the future.
Tieges et al. (2015)	DelApp	Smartphone application	Visual sustained attention	Proof-of-concept	156 older hospital inpatients (50 with delirium, 52 with dementia and 54 with no cognitive impairment). Age: IQR 70-91 years	Ability of smartphone based test of visual sustained attention to reliably differentiate patients with delirium from those with dementia.	DelApp scores differed significantly between all 3 groups (delirium < dementia < controls). ROC analyses revealed excellent accuracy of the DelApp for discriminating delirium from dementia (AUC = 0.93), and delirium from controls (AUC = 0.99).
<b>Wearables</b>							
Ahanathapillai et al. (2015)	Wrist Wearable Unit (WWU)	Smartwatch system	Activities of daily living	Proof-of-concept	Healthy younger adults. Age: range 20-50 years	Ability of system to detect and record activity related measures in order to infer behavioural patterns.	Activity level calculations from long term device usage, correlated with participants' self-reported activity levels.
Boletsis et al. (2015)	Basis B1 Smartwatch	Smartwatch system	Activities of daily living	Proof-of-concept	1 patient with advanced dementia and 1	Feasibility and validity of smartwatch-based measures to assess daily	Caregiver able to extract useful information about patterns in patient's behaviour (sleep, exertion) and changes to this pattern. Issue

					professional caregiver	activity function.	with steps not registering when patient used a walking frame support.
Browne et al. (2011)	SenseCam	Wearable camera system	Declarative memory	Proof-of-concept	1 adult with mild cognitive impairment. Age: 56 years	Efficacy of camera system to aid recall of significant personal events.	The proportion of events recalled was significantly higher over 2 weeks when using the SenseCam review (68%), than when relying on a diary (38%) or not actively cueing memory (30%). At 6 months this difference in recall between groups was still present.
Cachia et al. (2014)	WanderRep	Smartwatch system	Wandering	Proof-of-concept	1 patient with dementia and 5 professional caregivers	Ability of system to differentiate dangerous wandering scenarios from normal movement and activity.	WanderRep had a 78% sensitivity to detect pre-determined dangerous scenarios based on temperature, activity level, location and time.
Firouzi et al. (2015)	Indicator-based Smart Glasses	Smart glasses	Navigation	Design	Not specified	Usability of smart glasses system to provide visual, navigational cues.	The most distinguishable positions, frequency and brightness of LED lights for forming visual cues were determined. Need to develop and pilot a user-friendly interface and more lightweight device.
Matthews et al. (2016)		Wearable camera system	Activities of daily living	Proof-of-concept	18 people with dementia (age: mean 78.6 years, SD $\pm$ 9.1) and their primary caregivers (age: mean 63.7)	Ability of the system to capture episodes of dementia-related behaviour or caregiving interactions.	A total of 341 hours of usable video was obtained, yielding capture of 248 salient events.

					years, SD $\pm$ 14.0)		
Netscher (2015)	Max	Smartwatch system	Activities of daily living	Proof-of-concept	13 healthy participants from the Dementia Care Ecosystem study	Ability of system to measure users' routine behavioural patterns and detect outliers or declining trends.	Room detection accuracy 96.1% $\pm$ 2.6%. Reliable behaviour modelling possible with missing data i.e. when the user forgot/chose not to wear the device.
Shin et al. (2014)	u-Healthcare	Smartwatch system	Activities of daily living	Proof-of-concept	8 participants	Ability of the system to monitor users' location, physical activity and sun exposure.	The system had on average a 94.7% accuracy in detecting steps. User profiles of activity were then produced based on steps, demographic information, GPS information and light sensor data.
Stubbs et al. (2017)		Wearable accelerometer system	Activities of daily living	Validated	274 community-dwelling older adults. Age: mean 74.52 years (SD $\pm$ 6.12)	Efficacy of objectively measured levels of physical activity to predict cognitive stability in older adults.	Light and moderate physical activity as measured by the accelerometer were both significantly associated with a reduced rate of cognitive decline over 2 years, with light physical activity associated independently.
Thorpe et al. (2016)		Smartphone applications and smartwatch system	Activities of daily living	Proof-of-concept	5 patients with dementia and their spouses. Age: range 61 to 73 years.	Usability of integrated wearable and smartphone system to assist people with dementia with completion of daily activities.	Scheduling, communication and orientation tasks had a 100% completion rate, but navigation/emergency help tasks had a 0% completion rate.

Smart Homes							
Arcelus et al. (2007)	Technology Assisted Friendly Environment for the Third age (TEFETA)	Smart home	Activities of daily living	Design	No formal data collection	Investigating the benefits and limitation of the design.	May provide more independence for users, be an economical alternative to 24 hour care, and able to detect subtle changes in behaviour. However it could be considered intrusive, be rejected by users uncomfortable with technology or users may develop a false dependency on the technology.
Hall et al. (2017)		Smart home	Activities of daily living	Validation	24 care staff, age: mean 39.75; 3 residents with dementia, age: mean 81.33; 9 relatives, age: mean 55.67	Explore facilitators and barriers to the implementation of monitoring technology.	Core reason for use was to enhance resident safety and freedom, outweighing ethical concerns; technology was perceived as simple to use, but staff wanted more formal training. Frequent alarms were generated and staff had to rely on contextual knowledge to decide when to respond.
Stravropoulos et al., (2016)	DemaWare2	Smart home data modelling framework	Activities of daily living	Validation	98 AD, MCI or control participants in lab environment (age: range 60–90); 2 amnesic and 2 dementia in residential environment	Evaluation of DemaWare2 modelling in recognising ADL in laboratory and residential environments.	Activity recognition recall and precision close to 82% in lab-environment and 83% and 76% (respectively) in residential environment for most ADL; however, recognition varies depending on ADL. Can differentiate cognitively healthy, MCI and AD patients with up to 84% accuracy. High user acceptability.

Ishii et al. (2016)	M2M (Machine-to-Machine)/ IoT (Internet of Things) platform	Smart home data modelling framework	Activities of daily living	Validation	Pseudo patient data	Evaluation of modelling platform in recognising ADL.	Accuracy rate in determining behaviour was between 80-100% for most activities but was lower (30-40% accuracy) for forgetting to turn off the TV.
Dawadi et al. (2013)		Smart home data modelling framework	Activities of daily living	Validation	16 dementia patients, 51 MCI and 196 cognitively healthy participants grouped in 4 age ranges	Evaluating modelling framework in making ADL performance predictions compared to clinical observations and capability of dementia status predictions.	A correlation ( $r=.54$ ) between the direct observation scores and predicted activity quality when combining scores from all 8 activities; individual activity correlations varied. Reasonable classification accuracy in classifying participants into groups: dementia and cognitively healthy but not MCI.
Lyons et al. (2015)	Oregon Center for Aging and Technology (ORCAT ECH)	Smart Home	Activities of daily living	Longitudinal cohort study	480 smart homes; Users over the age of 70, MMSE > 24, CDR < 0.5, on enrolment.	Presenting results from the last 8 years.	ADL results for sleep, computer use, medication adherence, movement, social engagement and a multi-domain approach have been used to predict outcomes such as low mood, loneliness, and cognitive function; potential shown to improve quality of patient data related to cognitive decline.
Kaye et al. (2014)	Oregon Center for Aging and Technology (ORCAT ECH)	Smart Home	Activity of daily living	Longitudinal cohort study	38 MCI patients, age: mean 84.6 (SD $\pm 4.8$ ), 75 cognitively healthy	Assessing ability of unobtrusive smart home to monitor computer use, detect mild functional	No difference in computer use at baseline, but years 2 and 3 showed significant decrease in number of days with use, mean daily use and increase in day-to-day variability in computer use for MCI compared

					older adults, age: mean 84.6 (SD $\pm 4.3$ )	changes and identify MCI.	to healthy participants; indicating computer use can differentiate individuals with MCI.
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