Title: Health Monitoring Using Smart Home and Active Assisted Living (AAL) Technologies: A Scoping Review

Kirti Sundar Sahu, Arlene Oetomo, Plinio P. Morita

Submitted to: Journal of Medical Internet Research
on: February 16, 2022

Table of Contents

Title: Health Monitoring Using Smart Home and Active Assisted Living (AAL) Technologies: A Scoping Review

Kirti Sundar Sahu[1] MPH, MPT; Arlene Oetomo[1] BSc; Plinio P. Morita[1, 2, 3, 4, 5] PhD, PEng

[1]University of Waterloo, School of Public Health Sciences Waterloo CA
[2]University of Toronto - Institute of Health Policy, Management, and Evaluation Toronto CA
[3]University of Waterloo - Research Institute of Aging Waterloo CA
[4]University of Waterloo - Department of Systems Design Engineering Waterloo CA
[5]University Health Network - eHealth Innovation Toronto CA

Corresponding Author:
Plinio P. Morita PhD, PEng
University of Waterloo, School of Public Health Sciences
200 University Avenue West
Waterloo
CA

Abstract

Background: The Internet of Things (IoT) has become more integrated into everyday life, with devices becoming permanent fixtures in many homes. As countries face increasingly older populations, the use of IoT devices to support independent living for elderly individuals and others who need support is now possible. These groups may require assistance or varying levels of monitoring within the home. Smart home technologies that are unobtrusive, continuous, and reliably monitor healthy behaviour can fill this gap. The rationale of this scoping review is to provide insight into this evolving field of research by surveying the technologies available for in-home monitoring.

Objective: This scoping review evaluated smart home technology approaches to identify behavioural patterns and health indicators that could support caregivers and healthcare providers with standardized guidelines.

Methods: The study used the methodological framework proposed by Arksey and O'Malley. We analyzed articles published between 2008 and 2021 to understand better the scope of smart home data used to monitor vulnerable populations. Interest in smart home research increased rapidly after 2008, as technologies became more widely available. Only journal articles in English were included from PubMed, Scopus, ScienceDirect, and CINAHL databases. Search terms included smart home, ambient assisted living, health, and monitor.

Results: Forty-nine of the most recent and relevant articles were included in this scoping review. Most of the studies were from Europe and North America. The largest proportion of the studies were proof of concept, pilot studies, and related to the development of infrastructure architecture and testing of algorithms. Findings from these studies have been summarised by human-centric and techno-centric features. Nearly 78% of the studies have data from humans, 63 % mentioned age, and only 33 % mentioned the sex of the participants. Most of the studies had data from the elderly population (primarily female subjects) in the home setting. Nearly 60 % of the studies reported on the health status of the participants. Technocentric features included the type of data collected, the type of sensors used and analysis methods, respectively. A wide range of sensors were used across the studies, as were the variety of outcomes measured by each representing different health indicators. PIR sensors were the frequently used sensors, while activity or motion detection and recognition were the commonly used health parameters. There were many technical challenges and barriers, including a lack of collaboration and use of interdisciplinary approaches. There is no standardized definition of a smart home in the literature, and, thus, the authors proposed a new definition.

Conclusions: In conclusion, smart home technology has the potential to improve the monitoring of vulnerable populations, especially those ageing in the community, but it has not been fully explored. The use of Big Data, artificial intelligence algorithms, including machine and deep learning, with near-real-time dissemination of the results, will be the future of in-home health monitoring.

(JMIR Preprints 16/02/2022:37347)
DOI: https://doi.org/10.2196/preprints.37347

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✔ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✔ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Review

Title: Health Monitoring Using Smart Home and Active Assisted Living (AAL) Technologies: A Scoping Review

Sahu, Kirti S[1]., Oetomo, Arlene[1], Morita, Plinio P.[1,2,3,4,5,*]

1 University of Waterloo - School of Public Health Sciences
2 University of Toronto - Institute of Health Policy, Management, and Evaluation
3 University of Waterloo - Research Institute of Aging
4 University of Waterloo - Department of Systems Design Engineering
5 University Health Network - eHealth Innovation

* **Correspondence:** Plinio Pelegrini Morita, Ph.D., PEng
School of Public Health Sciences
University of Waterloo
200 University Avenue West
Waterloo, ON, N2L 3G1
Canada Phone: 1 5198884567 ext. 31372
Fax: 1 519 746 6776
Email: plinio.morita@uwaterloo.ca

Abstract

Background:
The Internet of Things (IoT) has become more integrated into everyday life, with devices becoming permanent fixtures in many homes. As countries face increasingly older populations, the use of IoT devices to support independent living for elderly individuals and others who need support is now possible. These groups may require assistance or varying levels of monitoring within the home. Smart home technologies that are unobtrusive, continuous, and reliably monitor healthy behaviour can fill this gap. The rationale of this scoping review is to provide insight into this evolving field of research by surveying the technologies available for in-home monitoring.

Objectives:
This scoping review evaluated smart home technology approaches to identify behavioural patterns and health indicators that could support caregivers and healthcare providers with standardized guidelines.

Methods:
The study used the methodological framework proposed by Arksey and O'Malley. We analyzed articles published between 2008 and 2021 to understand better the scope of smart home data

used to monitor vulnerable populations. Interest in smart home research increased rapidly after 2008, as technologies became more widely available. Only journal articles in English were included from PubMed, Scopus, ScienceDirect, and CINAHL databases. Search terms included smart home, ambient assisted living, health, and monitor.

Results and Discussion:
Forty-nine of the most recent and relevant articles were included in this scoping review. Most of the studies were from Europe and North America. The largest proportion of the studies were proof of concept, pilot studies, and related to the development of infrastructure architecture and testing of algorithms. Findings from these studies have been summarised by human-centric and techno-centric features. Nearly 78% of the studies have data from humans, 63 % mentioned age, and only 33 % mentioned the sex of the participants. Most of the studies had data from the elderly population (primarily female subjects) in the home setting. Nearly 60 % of the studies reported on the health status of the participants. Technocentric features included the type of data collected, the type of sensors used and analysis methods, respectively. A wide range of sensors were used across the studies, as were the variety of outcomes measured by each representing different health indicators. PIR sensors were the frequently used sensors, while activity or motion detection and recognition were the commonly used health parameters. There were many technical challenges and barriers, including a lack of collaboration and use of interdisciplinary approaches. There is no standardized definition of a smart home in the literature, and, thus, the authors proposed a new definition.

Conclusions:
In conclusion, smart home technology has the potential to improve the monitoring of vulnerable populations, especially those ageing in the community, but it has not been fully explored. The use of Big Data, artificial intelligence algorithms, including machine and deep learning, with near-real-time dissemination of the results, will be the future of in-home health monitoring.

Keywords: health*, monitor*, "smart home*", "ambient assisted living", "active assisted living", AAL

Introduction

Smart home (SH) technology employs the Internet of Things (IoT) concept to establish a connected system of interconnected devices that share data amongst themselves and automate actions to provide convenience and comfort while simplifying the homeowner's life [1,2]. This technology ranges from video-monitoring, alarms, smart planners or calendars, and reminder solutions to assist residents with their daily activities, thus improving their quality of life [3]. Advancements in smart home technology have led to the development of unobtrusive sensor technology, which can collect data to assess the overall health of residents [4]. These sensors exist in a Wi-Fi-based WSN environment (wireless sensor network), collecting various data [5]. These include passive infrared (PIR) sensors for motion detection, magnetic contact sensors to monitor open/close states of objects, bed occupancy sensors to trace sleeping patterns, chair occupancy sensors to observe sedentary periods, toilet presence sensors to track daily toilet use, fridge sensors to detect openings of the fridge door, and power meters to monitor appliance use [5]. These sensors are connected to the cloud, allowing for the rapid and near real-time transmission of data.

SH systems work by capturing the behaviours of an individual through software and hardware components [6]. This remote monitoring entails using sensors to collect data about the residents and the home, further used for behaviour change detection (BCD). The data collected by the SH sensors is analyzed to track residents' health conditions and predict their actions. An advantage of using SH sensors to collect such data is that they allow the residents to maintain their independence, privacy, and routines. This improves the efficiency and validity of functional health assessments because it provides a complete view of the resident's behaviour in a real-world environment.

Furthermore, people spend the majority of their time at home, allowing for the collection of accurate daily-behaviour data [4]. This minimizes the distance between development and real-world application, as these technologies are easily integrated into people's lives and can provide high-quality data. Many current ambient-assisted living systems (AAL) use intrusive and costly equipment such as cameras and wearables or prohibitive sensor nodes that are complex to configure. However, recent developments in microcontroller technologies have resulted in opportunities for SH automation [7]. These new developments point to the potential for high-quality, cost-effective AAL systems such as Ubicare, as presented by Dasios et al. [7].

Smart home technologies can be leveraged for a variety of purposes, including energy-saving [8], security and safety [9], fall detection [10], light management [11], and fire detection [12]. Independence prompting technologies, designed specifically for elderly individuals, enable people to continue living independently. Through continuous behavioural monitoring, leading to the early diagnosis of potential health problems and the detection of hazardous events (such as falls), older adults and other vulnerable persons can benefit from SH monitoring which supports independent living and a higher quality of life [7,13]. Other applications of SH technology include research into the assessment of psychological health in older adults through monitoring their behavioural data. Overall health predictors such as physical activity and sleep can also be determined through smart home-based data [4]. Furthermore, SH technology can be used in monitoring behaviour changes in vulnerable populations. For example, monitoring behavioural impact following health events such as cancer treatments or injuries can provide insight into the effectiveness of treatments [14].

With the onset of the COVID-19 pandemic, the potential usefulness of smart homes increased, specifically due to the high mortality and morbidity associated with long-term care homes; technology could have been used on a large scale to support an overwhelmed workforce [15]. Analyzing SH-based behavioural data for older adults may assist in the detection of the onset and progression of age-related diseases [4], since ageing is associated with cognitive and physical decline [4].

This research project aims to perform a scoping review on approaches that leverage SH technologies to identify behavioural patterns and health indicators that could be used by caregivers and healthcare providers, with the goal of understanding discrepancies between technologies' development and real-world applications to propose effective solutions.

Methods:

This scoping review is based on the widely accepted framework by Arksey and O'Malley used across many disciplines [16]. This framework allows for the inclusion of a range of methodological designs from different disciplines as this is an interdisciplinary field. As such, it was selected as a suitable method for exploring the area of SH technology for public health surveillance. Using the framework, the researchers developed a research question, identified relevant studies, completed charting, summarized findings, and reported results [16]. The researchers communicated frequently to ensure charting consistency [17–19].

Research Questions: The following questions guided this scoping review:

RQ1. What smart home technologies are currently being used to monitor health care indicators for vulnerable populations at home or in the community?
RQ2. What types of information are these sensors gathering?
RQ3. What insights can be generated from these datasets?

The goal of the study was to synthesize the literature and identify gaps or opportunities in smart home technology to inform practice, policymaking, and research.

Data Sources and Search Strategy:

We searched four databases: PubMed, Scopus, ScienceDirect, and CINAHL. As this literature related to our original question was limited to publications between 2008 and 2021, and only texts in English were included. This field began to develop in earnest from 2008 onwards. Only peer-reviewed published journal articles were selected. The search strategy established trends of the following search terms: *health, monitor, smart home, ambient assisted living, active assisted living, AAL*. Please see our Search Strategy in the supplemental material-1 for the search term queries used. Of note, the term "surveillance" was not used as its inclusion returned hundreds of results outside of the scope of this research project.

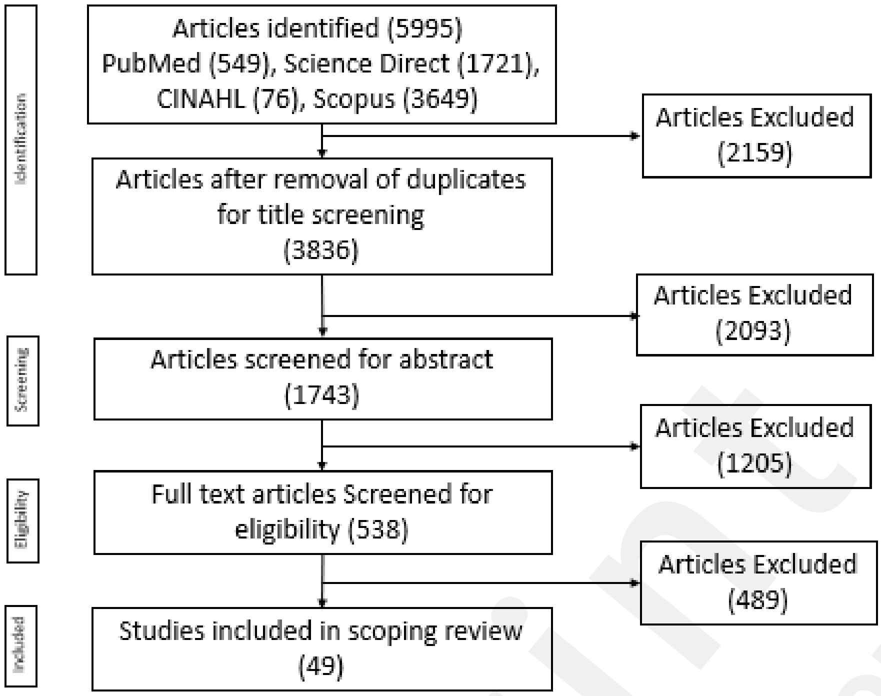


Figure 1: PRISMA Flow Chart - Systematic Study Selection

Selection Process

The search was completed in August 2021 and returned 5995 potential articles matching the designated search terms. Two thousand one hundred fifty-nine duplicates were removed, leaving 3836 articles that were title screened. These articles were then grouped according to the year of publication. Researchers (AO and KS) selected 538 articles to be discussed for inclusion based on abstracts that met the inclusion criteria.

Selected articles had to contain both environmental/remote sensor technology and application of described systems in real-world scenarios (e.g., tested in a home setting). Conference proceedings and articles that focused on gait measurement and dementia diagnosis were excluded, as were articles that contained robotics, wearable technologies only, and mobile-based health applications.

The present study used Mendeley [20] and Zotero [21], two reference manager software used to organize the full-text articles for the scoping review.

Results:

After the screening, 538 articles were selected for full-text review by AO and KS in Mendeley. The authors, however, switched to Zotero to manage the files due to software issues. Both researchers selected 29 articles on the first attempt and 97 articles with conflicts. The articles with conflicting votes were discussed case-by-case until a unanimous decision was reached, and 20 were selected. The result was 49 papers eligible for the scoping review. During this process, the research questions and inclusion and exclusion criteria were further refined. The study flow can be seen in Figure 1.

The key characteristics of the 49 studies published between 2008 – 2021 are described below. We begin by describing the study characteristics of the papers, followed by the human-centric descriptions and technocentric descriptions.

Study characteristics

We began by looking at the type of study, country of origin, year of publication, and association with academic institutions. Our results showed that all studies fell under eleven broad types of studies, as shown in Table 1.

Table 1: Profile of selected studies by type, country, and human participation

Type of Study	By Country of Research	Sample Size	Demographic Profile of the Participants	Participant Health Profile
Pilot Study (N=13)	**USA**			
	[22]	11	18+	Healthy
	[23]	5	45+,2 Males, 3 Females	SCI, Muscular Dystrophy, Multiple Sclerosis, Polio
	[24]	10	55+	Chronic Diseases
	[25]	34	70+	Chronic Diseases
	[26]	263	18+, 72 Males, 191 Females	Healthy
	[27]	37	65+, 7 Males, 30 Females	Chronic Diseases
	[28]	6	No Data	No Data
	Italy			
	[29]	32	No Data	Healthy and Cardiac Conditions
	[30]	13	65+	Healthy
	Switzerland			
	[31]	13	65+	No Data
	Greece			
	[7]	2	70+,1 Male, 1 Female	Healthy
	Portugal And Spain [32]	23	30+,11 Males, 12 Females	Healthy
	China			

	[33]	1	65+Female	Chronic Diseases
Proof of Concept (N=7)	**USA** [34] [4] **Egypt** [35] **Iran** [36] **Korea** [37] **Spain** [38] **UK** [39]	20 29 0 1 22 0 1	65+ 18+ N/A 65+ 60+,10 Males, 12 Females N/A No Data	Depression Healthy N/A No Data No Data N/A Healthy
Algorithm Evaluation	**USA** [40] [41] [42] **Germany** [43] **Sweden** [44] **UK** [45]	1 40 40 0 19 12	18+ 18+ No Data N/A No Data No Data	Healthy Healthy Healthy N/A No Data Dementia
Proposal	**Spain** [46] [47] **India** [48] **Korea** [49] **South Africa** [50]	 0 0 0 150 0	 N/A N/A N/A 60+, 23 Males, 127 Females N/A	 N/A N/A N/A Healthy N/A
Technical Validation	**Italy** [51] [5] **Germany** [36] **USA** [52]	0 0 10 22	N/A N/A 18+, 7 Males, 3 Females 45+, 7 Males, 15 Females	N/A N/A Healthy Healthy
Case Studies (N=4)	**USA** [14] **Greece** [53] **Slovenia** [54] **Taiwan** [55]	3 4 0 1	70+ Female 70+, 1 Male, 3 Females N/A 60+ Female	Lung Cancer, Insomnia, Leg Pain Amnestic, Mild Cognitive Impairment, Dementia N/A Healthy
Method Evaluative (N=3)	**Australia** [56] **France** [57] **Italy** [58]	 0 13 17	 N/A 18+ 18+	 N/A Healthy Healthy

Longitudinal Study(N=3)	**USA** [59] [60] [61]	 11 16 480	 65+ 70+, 3 Male, 13 Females 70+	 No Data Healthy No Data
Platform Evaluation(N=2)	**Finland** [62] **Greece** [63]	2 207	70+, 1 Male, 1 Female 65+	Healthy and Hip Surgery Rehabilitation Frailty
Qualitative Study(N=1)	**Ireland** [64]	78	18+, 69 Males, 9 Females	Healthy
RCT (N=1) (Secondary Data Analysis)	**Italy** [5]	200	No Data	No Data

N/A- Not Applicable

Among the 49 articles, 31% were pilot studies (n=15), 12% were both proof of concepts and algorithm evaluations (n=6), 10% were proposals (n=5), 8% were technical validations (n=4), 8% were case studies (n=4), 6% were method evaluations (n=3) and 6% were longitudinal studies (n=3), 4% were platform evaluations (n=2), one (2%) randomized controlled trial (RCT), and one (2%) qualitative study. The research was global with 47% (n = 23) of the articles originating from Europe, followed by 35% (n = 17) from North America. Twelve percent of the studies were from Asia (n=6), four percent were from Africa (n=2), while two percent were from Oceania (n=1).

Similarly, when classified based on the year of publication, more articles appear to have been published in recent years than in past years, that is, 71% (n = 35) of the articles were published within the last five years (2015 - 2020), while 29% (n = 14) of the articles were published pre-2015, as shown in Figure 2.

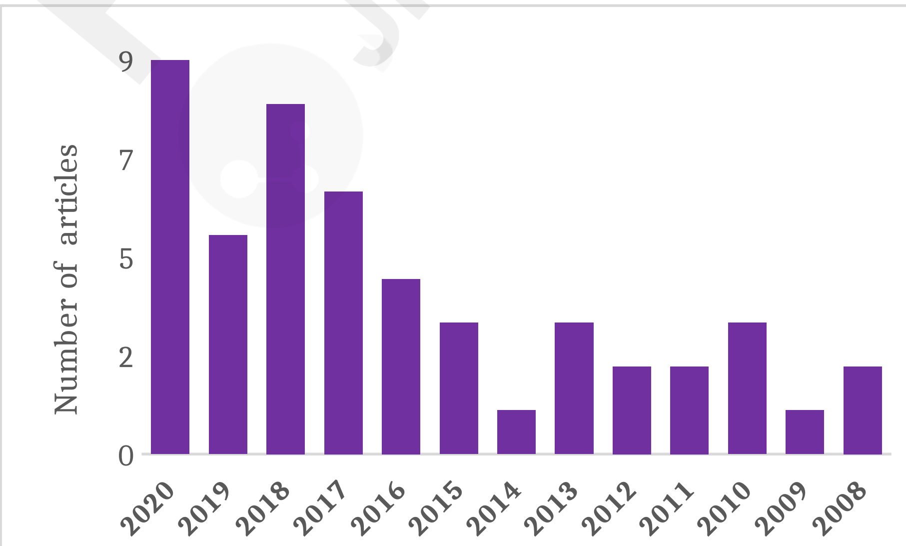


Figure 2: Articles by year of publication

All of the studies were either directly or indirectly related to academic institutions.

The domain of publication:

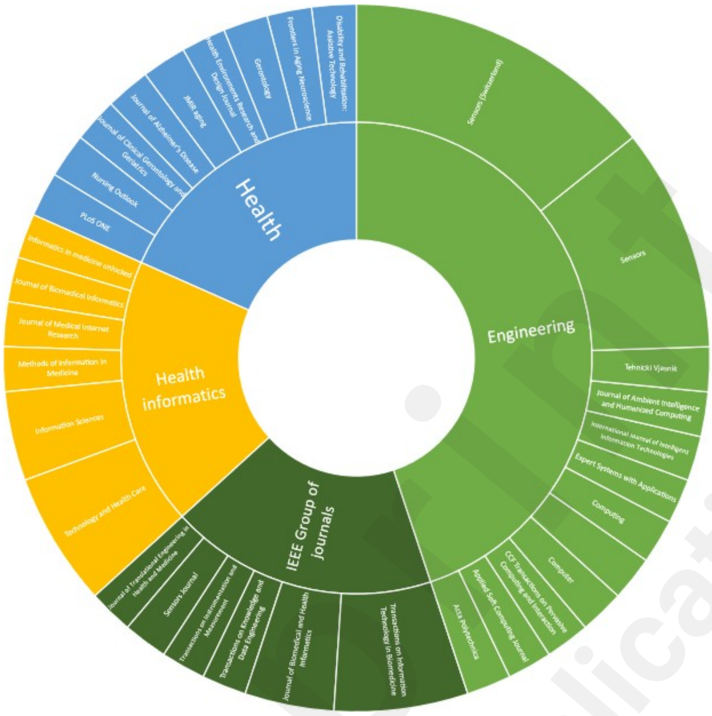


Figure 3: Journals of publication

When classified based on a publication's domain, 64% of the selected articles were published primarily in the fields of engineering and computer science (n = 31), 18% were from biomedical engineering and health informatics (n = 9), and 18% came from health-related journals (n = 9) (see the Figure 3 and Supplementary Table 2).

Keywords:

Figure 4 shows the keywords from the 49 articles included in the scoping review, visually assembled in a word cloud. The font size of the words was scaled in proportion to their frequency. The most used words were "smart home(s)" followed closely by "ambient assisted living", and "intelligent". Words in the smallest font and on the edge of the figure, while less prevalent, featured at the intersections of various fields within the humanities and technology.

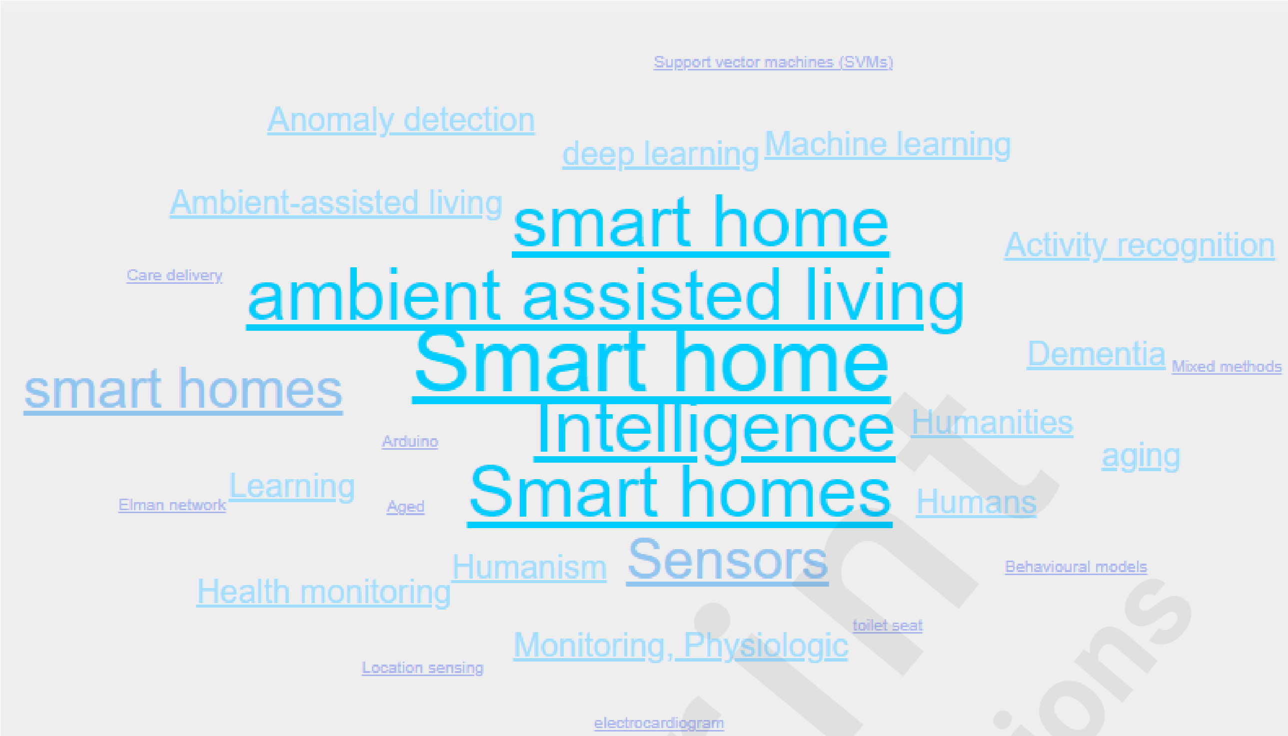


Figure 4: Word cloud of article keywords

Humancentric features

Populations studied:

Within the 49 studies, 38 studies (78%) used data collected from 1,849 human subjects, whereas the remaining 11 (22%) studies used simulated data for platform or algorithm evaluation (Table 1). The ages of these participants ranged from 18 to 93 years. Out of 38 human subject studies, 31 (63%) studies mentioned age, and 16 (33%) studies mentioned the gender of the participants. Female subjects were nearly three times more prevalent than male subjects (425 female versus 145 male). Some studies recruited healthy volunteers among students (Table 1). Other studies recruited patients from memory care units and assisted-living residents. Thirty (79%) out of 38 studies reported the health status of participants, by indicating whether the subjects were healthy volunteers or had ongoing pathological health problems (e.g., dementia, Alzheimer's disease, mild cognitive impairment, chronic diseases, depression, hip surgery rehabilitation, lung cancer, insomnia, spinal cord injury, muscular dystrophy, multiple sclerosis, poliomyelitis, cardiac conditions, frailty, or leg pain).

Technocentric features

The primary focus of each article is described in Table 2. Most of the articles focused on recognizing human mobility patterns in the room by analyzing data from the PIR sensors and other categories of data. One of the articles focused on services for healthy elderly individuals [32], whereas another study emphasized home monitoring systems during the quarantine required by the COVID-19 pandemic [50].

Table 2: Technical components of the selected articles with outcomes

Type of study	Country of research	Primary focus	Outcome measure	Algorithm	Type of data	Key finding	Challenge
A pilot study (n=13)	USA [22] [23] [24] [25] [26] [27] [28] Italy [29] [30] Switzerland [31] Greece [7] China [33]	Independent living for the elderly population who may or may not have chronic diseases.	Activity, fall detection, indoor motion	Statistical analysis of the machine learning algorithm	Binary sensors-motion, light, temperature, humidity,	All the studies said they were successful with their objectives. Monitoring of physical, social, and cognitive health of healthy persons or those with chronic diseases is possible using existing mechanisms. Multiple types of sensors can be integrated to build a central service, where monitoring/ early identification of abnormal events can be possible.	Differentiate individuals, False alarm
	Portugal and Spain [32]	E-service provision	Physical, medical, social interaction by audiovisual communication with service providers	Qualitative and quantitative data analysis	Interview questionnaire	Almost everyone was able to perform the tasks without any help or intervention.	Scalability
Proof of concept (n=7)	USA [34] [4] Egypt [35] Iran [36] Korea [37] Spain [38] UK [39]	From 2013 to 2020- the proof of concept improved from synthetic data to real-world data, single individual to multi-individual- but the objectives more or less – the same- activity recognition, anomaly detection, pattern	Motion or presence data	Binary sensor data- Machine learning algorithm- SVM as the typical model with many of the studies. The recent study used the Parallel Activity Log Inference Algorithm (PALIA).	Sensor data	Successfully proved their work, and all of them were working.	Real-world data with noise- Multi-person discrimination

		recognition to improve the quality of life of elderly individuals.					
Algorithm evaluation	USA [40] [41] [42] Germany [43] Sweden [44] UK [45]	All of the studies tried to recognize normal activity patterns and find out abnormal or anomaly detection.	Motion or presence data device-free solutions based on radio signals like (home WiFi, in particular,802.11 channel state information (CSI)-2020-Damodaran	Machine learning and deep learning algorithm	PIR sensors	With time, the accuracy of the algorithms increased. Precision and sensitivity increase significantly when using preceding and partial oncoming sensor activations compared to when using only preceding sensor activation.	The real-time capabilities have become a key challenge in activity recognition to offer a tool that meets real-world conditions.
Proposal	Spain [46] [47] India [48] Korea [49] South Africa [50]	Activity recognition of the individual	Mobility pattern recognition	Machine learning, deep learning algorithms	Binary sensors data Acoustic sensors data	Better performance in abnormality detection than that of the existing systems Monitoring the patient in real-time which reduces hospital costs and exposure of patients to highly contagious diseases like Covid-19	

Technical validation	Italy [51] [65] Germany [36] USA [52]	AAL monitoring Intelligent toilet seat Differentiate regular patterns and identify abnormalities in household activities	PIR sensors, magnetic contact, bed occupancy, chair occupancy, toilet presence, fridge sensor electrocardiogram and bioimpedance spectroscopy measurements behavioural monitoring by presence data	Behaviour explanatory models (BEM), Sensor profiles (SP) and multivariate habits clusters (MHC) R-peak detection SAMCAD/ CAR	Motion sensor data electrocardiogram (ECG) and bioimpedance spectroscopy (BIS) PIR sensor	Convincing proof-of-concept test, demonstrating the ability to elicit expressive indications from indirect, continuous monitoring, fully autonomous. The intelligent toilet has a high potential to increase the quality of medical care for older adults living at home by keeping track of important health and nutrition parameters. The system can model behavioural patterns, detect deviations that may be consistent with disease onset.	These test methods are not diagnostic modes. We need to test the same with a real-world scenario. Only indoor activity can be monitored and discriminating multiple individuals in a single room.
Case studies (n=4)	USA [14] Greece [53] Taiwan [55] Slovenia [54]	Behaviour change detection Home monitoring system Activity recognition effective active home automation solution based on open-source home automation software and wireless, custom developed, WiFi-based hardware.	Activity change sleep, physical activity, and (activities of daily living) ADL Automatic classification of ADL System functionality	CASAS middleware	Motion. Light temp, door Motion, presence, utility usage sensors PIR/ Current sensors	Smart-home and machine-learning technologies can be used to understand the behavioural impacts of health events. Successful measurement of daily activities	Recalling retrospective data, sensors can be updated, heterogeneity in data collection. Data was collected from the household member of the author. Unable to distinguish visitor/ cohabitant Case study without human subject

							involvement
Method evaluative (n=3)	Australia [56] France [57] Italy [58]	Activity recognition	Automatic classification of ADL	SVM Unsupervised machine learning Rule-based reasoning method for activity recognition	Location, temperature, sound, postural transitions and walk periods Motion sensor location, activity, motion	The cross-validation test gave preliminary results with a classification rate of 75% for a polynomial kernel and 86% for a Gaussian kernel with an adapted parameter. The night-time period was found to be adequate in capturing baseline behaviour patterns. The minimal number of days needed to establish baseline user behaviour patterns is 55 The recognition accuracy outperformed well-known methods.	Real-world location multi-occupancy noise
Longitudinal study(n=3)	USA [59] [60] [61]	Remote monitoring of pain Remote monitoring of loneliness	Recognize pain-associated behaviours	ML algorithm, isolation forest (forest) anomaly detection algorithm/ Decision tree classifier logistic regression classifier	PIR based sensors data, light temp humidity	Effective for detecting clinically relevant pain-related behaviour, or changes relevant to those behaviours Prediction of loneliness possible using sensor data	Data security and privacy Distinguishing individuals within the home
Platform evaluation(n=2)	Greece [63] Finland [62]	Remote patient monitoring using home health or telehealth	Interoperability/ adaptability which can accommodate different types of sensors	Rule-based ontological framework Partial human	PIR based sensors data	2010 study was with two patients, whereas the 2015 study tested more	To discriminate the presence of external persons in the patient's

				monitoring is required.		than 200 frail patients. Using these patient-reported enhanced senses of security. Positive outcome towards combined monitoring early detection of health events.	indoor environment, such as visitors, in order to reassure the correctness of the collected activity information, always in an as unobtrusive as possible manner.
Qualitative study(n=1)	Ireland [64]	Identify and validate the requirements for new technology enabling resident wellness and person-centred care delivery in a residential care environment	State of environment and state of care delivery, state of resident	Qualitative data analysis and machine learning algorithm	Sensor and interview data	Participants have control over a particular aspect of their life. - sense of comfort	Additional research is required with older adults with diverse age-related physical, sensory and cognitive challenges
RCT (n=1) (Secondary data analysis)	Italy [5]	IoT based home monitoring for elderly stroke patients	Behavioural aspects-bed/rests patterns, toilet usage, room presence and many others	Regression framework and anomaly detection unsupervised clustering techniques	Sensor data	Successful	Scaling up of these findings to broader systems

Study setting:

The research included studies that took place primarily in real-world settings. Some of the studies used simulated home environments. If the study took place in an apartment, the number of rooms typically used were between two and three. Studies used simulated environment setups, smart home testbeds, smart apartments, or smart workplace environments. Typically, the study participant was either alone or the single occupant of the home/unit.

Length of study:

The length of study ranged from a single day of data collection to eight years.

Outcome measure:
Different types of sensors, as described in Table 3, can be grouped into three main categories: utilization of space (bed and chair occupancy, toilet, fridge, kitchen, or GPS), human vitals (blood pressure, ECG, blood glucose, heart rate, or respiratory rate), and environmental sensors (light, temperature, humidity, sound, airflow, smoke, carbon monoxide, gas, or flooding).

The technology used:
Most of the sensors were based on PIR, most commonly used for motion detection. Used in homes and businesses for lighting, PIR is economical, energy-efficient, and reliable.

Type of data:
The most common type of data was binary (Y/N) from motion or object presence sensors, audiovisual (sound, light) and continuous data from vital indicators and environmental (heart rate, respiratory, blood glucose, temperature, humidity), spatial-temporal data (GPS).

Data management:
SQL or MYSQL databases were frequently used in the selected articles to organize the data, whereas MATLAB and Python were mainly used for data analysis and visualization.

Methods of Analysis:
Various statistical methods were used, including descriptive statistics, model building, machine learning, and deep learning. The majority of the studies utilized descriptive statistics to describe the demographic characteristics of the study population and other associated factors of research participants. Multi-domain approaches [57], longitudinal linear mixed-effect regression [60], and out-of-sample cross-validation methods [60] were used.

Several studies employed machine learning (ML) algorithms including AdaBoost, Bayes network, boosting model using ensemble, Circadian Activity Rhythms (CAR), clustering, conditional random field, context-aware reasoning, decision tree emerging pattern, fuzzy logic, Hidden Markov Model (HMM), multi-HMM, K-Nearest Neighbors (KNN), logistic regression classifier, Multilayer Perception, Multiple Regression Model, multivariate habit cluster, ontological modelling, SAMCAD II, Support Vector Machines (SVM), and SVM Naive Bayes classification to identify a regular pattern and predict future patterns. The models listed above are supervised or unsupervised, predictive models, whereas some are exploratory models.

Several deep learning methods were also used, including artificial neural networks (ANN), Activity recognition using Discontinuous Varied-Order Sequential Model (DVSM), Convolutional neural networks (CNN), Echo state networks, latent trajectory models, longitudinal linear mixed-effect regression RNN, open pass neural networks, recurrent neural networks (RNN), and sequence to sequence.

One study used mixed-methods and included a thematic analysis of the quantitative data.

Another study used the activity discovery method, and yet another conducted a qualitative data analysis using a mixed-method approach. Some studies used induction algorithms, behavioural monitoring systems, Rapid Iterative Testing and Evaluation (RITE), or QRS recognition.

The outcomes measured through these sensors included: acoustic-event detection, activity recognition, behavioural monitoring, call-center activities, fall detection, functional health-decline/improvement, high-level ADLs/IADL, leisure services, loneliness, medical services, patient health-status, perception, physical activity, sedentary behaviours that included the use of TV, computer, sitting, medication adherence, movement patterns, sequence of gestures, sleep, and eating habits, situational awareness, social engagement, time spent outside the home, and overall well-being.

Table 3: Types of sensors, Data characteristics and their association with health

Sensor	Type of data	Health indicator/proxy
Motion - PIR, RFID, magnetic switches	Any movement within the room, door movement	Physical activity/ speed/quality of physical health
Presence	Any movement within the room, the indoor movement	Physical activity/gait speed/quality of physical health
Temperature	Temp of room, the temp of stove/oven	Body temp - Health quality / activity- sleep / awake / sedentary
Light	Luminosity - lux	Sleep / active
Sound/microphone	Noise	Sleep / active
Humidity	Indoor environment	Indoor environment
Biosensors	Fall detection	Activity / alert
Plug sensors	Appliance use - TV, fridge, kitchen appliance, medicine dispenser	Activity
Body position sensors	Activity	Activity
Carbon monoxide (CO)	Indoor environment	Indoor environment
Flooding sensors	Water use / consumption	Indoor environment
Gas sensors	Use of gas in the kitchen	Indoor environment
Smoke detector	Indoor environment	Indoor environment
Pressure sensor / smart tiles / pressure pad	Bed movement, gait speed, chair movement	Sleep time / quality
ECG patch	Heart health	Heart health
Airflow sensors	Room environment	Indoor environment
SPO2	Oxygen saturation of blood	Heart health

Blood pressure (BP)	Heart health	Heart health
Heart rate (HR)	Heart health	Heart health
Respiratory rate	Lung health	Lung health
Blood-glucose sensors	Overall Health	Diabetes
Smart weighing scale	Bodyweight	Weight
Pedometer	Walking	Physical activity
Contact sensors	Usage of a phone book, cooking pot, medicine container	Activity analysis
GPS	Location	Location
Wi-Fi Signal	Indoor activity	Location
Smart seismic sensor	Floor Vibration	Activity analysis, including fall

Overall observations:

The 49 papers included in this review can broadly be divided into two groups: one which approached the use of IoT for health purposes and the other which used IoT for technological validations.

All the studies reported in their findings that IoT helped improve quality of care, increased participants' sense of comfort, and enabled the recognition of early identifiers or signs of a problem, increased their understanding of the impact of health events on overall health, and measured daily activities.

The biggest challenge faced by the researchers was differentiating between multiple participants in a single space. The second challenge identified was the lack of interoperability amongst technologies and the ability to scale up. The third challenge identified was linked to data security and privacy.

Additional challenges identified by the researchers included: calibration of the sensors, cost of technology and data management, data streaming and integration, data velocity, data volume, difficulty differentiating activities, generalization of activities, i.e., data collected from young volunteers while algorithms were designed for the elderly population. Heterogeneity, inability to differentiate between multiple residents within a single house, installation of the sensors, lack of patient motivation, large numbers of nodes, limited data bandwidth, limited to indoor activities, malfunctioning sensors, privacy, sample size, security, service quality, user acceptance, and varying levels of data accuracy were also noted as challenge.

Discussion:

The goal of this review was to understand how smart home technologies were being used within the healthcare space for the purposes of monitoring individuals in their homes. Previous literature reviews of the application of smart homes for health, published in 2012 and 2017,

suggested that an existing review of smart homes exclusively for comprehensive health was missing [1,2]. If at all present, they represented a very narrow subsection within healthcare focused on geriatric care [66] and more specific health outcomes such as dementia [67,68], fall prevention [69], and pregnancy [70]. In 2016, a systematic review discussed literature on smart home for health in the elderly population that included data collected in 2014 [66]. Mohsen Amiribesheli's [71] survey from 2015, while neither scoping, systematic, or exhaustive, provided a complete overview of the techniques and technologies involved in smart homes, as did in this review from Wang et al. in 2021 [72].
Another systematic review reported that small-scale experimental setups were highly successful [69]. That study showed that telehealth combined with exercise programmes and smart home systems could reduce fall risk significantly (risk ratio=0.79, 95% CI [0.72, 0.86]). E-interventions also significantly improved balance and fall efficacy (standardized mean difference=0.28, 95% CI [0.04, 0.53]) [69].

Some of the other evidence presented, focused on technical aspects or ethical aspects of this domain, such as a review of a smart home for security [9], Internet of Things Architectures, Technologies, Applications, Challenges, and Future Directions for Enhanced Living Environments and Healthcare Systems: A Review [73]. Despite all the advantages of healthcare systems, several open issues exist, such as availability, reliability, mobility, performance, scalability, and interoperability, among others. As the evolution of society will not stop, these will be ongoing open challenges because the use case scenarios will continue to evolve. It is essential to note that this kind of care system can exist to support medical treatments and as an essential complement to medical supervision. This paper has presented relevant aspects of IoT for healthcare systems, such as open-source platforms, operating systems, and open issues. Digital healthcare requires a paradigm shift. Beginning with a thematic overview introducing Health and IT professionals and engineers, and students to new ways of providing care and support.
Notably, several themes emerged from the review of the current literature about the framing of the research (health versus technology) and the source of these characteristics. This is a rapidly growing interdisciplinary field at the intersection of health, information technology, and engineering. Much of the research is in its early stages, with technology becoming more prevalent in our lives through miniaturization and affordability. As the total size of the data collected through IoT is ever-increasing, this leads to challenges related to the management, storage, security, and privacy of the data. A wide range of analytical methods are also being utilized, with descriptive statistics being replaced by machine learning and more advanced algorithms, such as deep learning. (We hope that these insights will help guide research efforts in this evolving field as the potential of smart homes for healthcare has yet to be fully realized).

Defining a smart home for healthcare:

Many articles did not include a concrete definition of a smart home (SH) upon reading the studies in question. Those that did include similar definitions, defining a space as indoor (house, home, dwelling), outfitted with technology (sensors) that can collect (observe) behavioural data (activities) continuously, without interfering in daily life routines while also improving individuals' quality of life (maintaining autonomy, preventing harm, or abnormality detection).

Based on the wide range of categories of studies and increase in publication numbers in the past few years, it is evident that this is a rapidly evolving field of research [75]. Most of the articles were published in engineering and information technology journals. However, the primary audience is in the healthcare field. This mismatch creates a gap that must be bridged before any implementation of findings. Because of the highly interdisciplinary nature of this work, any research team should include a broad spectrum of skills and domain knowledge experts.

Western developed nations dominate this field's progress, which aligns with ageing trends in these countries and the adoption of the technologies in all areas of life, continuing the trend of increasing the health and knowledge inequality between low- and middle-income countries (LMICs). This innovation is primarily driven by policies and the general public interest to improve the quality of life. Since many LMICs focus on reducing mortality and morbidity related to infectious diseases, they do not have the resources to prepare for an ageing population that will appear following eminent epidemiological [76,77] and demographic [77,78] transitions. Researchers and funding bodies should ensure that LMICs can develop these technologies, dissolving since eliminating the digital divide.

Humancentric theme:

As smart homes support humans, all research should, at a minimum, report the demographic characteristics of human participants: including health status, age, gender, and race. The lack of involvement from individuals with a health background within the research team creates more social and health inequities. Traditional technical training does not consider health outcomes, and inequality between groups, like social determinants of health, is overlooked. Health and epidemiological research are grounded in demographic data; without it, the implementation of results is nearly impossible, and results will likely be disregarded.

Furthermore, computer science or engineering research uses simulated or fabricated data due to budget, people power, and time constraints. This method is highly efficient when the resources mentioned above are lacking, as many new analysis methods rely on large datasets. However, researchers must be aware of potential biases that can enter data and algorithms. Recent examples come to mind of biased algorithms that viewed Black patients as considerably sicker than White patients [79], or how facial-analysis programs attributed skin-type and gender biases to women with darker skin tones [80]. Healthcare must also confront racism within the system [81–83], and attention to ensure digital solutions do not reproduce and continue to harm historically oppressed and underserved individuals is essential.

Technocentric theme:

The rapid introduction of new technologies in daily life signals the exceptional rate of technological evolution and saturation. With new methods developed to manage growing datasets, the primary analysis methods are MATLAB and Python. The most commonly used databases are SQL and MySQL within these technical fields since they are relational by design. Due to increasing demand for dataset volumes use techniques like machine learning, deep learning, and other specialized techniques within artificial intelligence are better suited for big data analysis. Researchers can use tools to handle vast quantities of data quickly and efficiently instead of traditional health statistics methods, including models limited to smaller datasets.

Still, there is a lack of collaboration and interdisciplinary work between health and technical fields as evidenced by tools and databases used and publication journals. Many of the articles included in this scoping review contained highly technical language. Without prior expertise in these fields, translation into "lay person's" language is complex and potentially challenging even for health professionals who are already experts in their field. This may be due to the lack of training and skills education, policy, and facilitation of opportunities to collaborate with those in technology.

Older adults were the subjects of choice among the included studies. However, the age range of older adults varied depending on the location of the study as different countries had different definitions of seniors or older adults. Interestingly, female subjects were more prevalent, being nearly three times more likely to have been studied than male subjects. This is usually the opposite trend in research [84,85]. Some potential reasons for this variance could be that women live longer [1], are more likely to live in assisted care units [2], are more likely to participate in studies [3], or have altruistic considerations [4]. While some studies took place in home settings, none were unobtrusive studies or zero-effort. This means there were still disruptions to daily routines or else involved subject participation in logging activities. Zero-effort technologies in real-world situations require no additional effort on the part of the patient or caregiver; the system of data collection and analysis is automated [86].

In the technocentric theme, a wide variety of sensors was used to meet the differing needs of each study. This is evident in the different types of data collected and the measured outcomes of health indicators or respective proxy measures of quality of life, including physical and mental health. Each of the selected studies measured a particular health indicator (such as heart rate, physical activity, sleep, etc.). The health indicators collected were measurable in quantifiable units. For example, sleep and sedentary behaviour are measured in units of time and activities of daily living (ADL), and physical activity (mobility/gait) were measured via numerical scales. ADLs are evaluated based on standardized tests known as instruments of ADL (iADL) and are therefore much easier to evaluate. However, other health indicators, such as loneliness or mental health, cannot be quantified and thus must be measured using a proxy. AI will enhance the types of analyses possible, as this method relies on data from a vast number and variety of sensors. A smart home can monitor and measure the health of an individual. Multiple datasets can be integrated with the computing power available today, which can support a holistic understanding of human health.

As the technologies were still in the early phases of development, most articles focused on building the technological infrastructures, proof of concepts, pilot studies, and the selection of technologies. Based on the available evidence and identified gaps, we would like to propose the following definition for a smart home for healthcare:

"A smart home for healthcare can be defined as a home equipped with smart sensors using Bluetooth, Wi-Fi, or similar technology, not restricted to IoT, to automate, regulate, and monitor home occupants' physical health, mental health, and environments within the home. The main focus must be on convenience, safety, and improvement of one's quality of life, to address the needs of the individual, caregivers, and health professionals."

Strengths:

The main advantages of using IoT technologies are that they are real-time, and that data can be collected objectively from the source, making it less prone to performance and recall biases because there is no time delay. Data streams 24/7, 365 days a year to the cloud, and is immediately available for analysis. The analysis can be conducted automatically, and the resulting insights can be shared immediately with users. For example, many smart wearable trackers deliver daily insights about physical activity levels and sleep data to users. These can be powerful tools for motivating healthy behaviours and encouraging healthy behavioural changes. There is no subjective nature to the sensor data because it is done passively without human effort; one can go about their day, forgetting that they are wearing the device. If these insights can be shared with primary healthcare providers and caregivers, the additional insights will make caring for an ageing population much more comprehensive. These are important as this data can be used to inform care delivery, support evidence-based policymaking, and enhance care strategies with timely results and findings.

Challenges:

*M*ost of the studies had limited numbers of subjects involved due to resources and time constraints. Moreover, the use of synthetic data despite the availability of actual data highlights the limitation of data access and the need for better access to high-quality data. Additionally, many of these technologies were not diagnostic tools because the outcome measures were not quantifiable (video or audio). There was a lack of data integration which involved combining structured data with unstructured data. As this type of research utilizes time series data, there are additional challenges with data management that require careful planning and data cleaning.

Based on this literature survey, it is clear that technology is constantly being upgraded and improved with new products continually reaching the market. As companies compete to create the latest technology, much of the innovation is siloed. Due to this, interoperability becomes an issue; the various solutions are not compatible, requiring a third-party bridge that is either software or hardware based. Because there are no standardized guidelines, companies develop their protocols for handling data, unique architectures which contribute to the incompatibility across the IoT landscape. The result is a jungle of systems that are confusing and intimidating to navigate for many non-tech-savvy individuals. One must either subscribe to a single system that can be cost-prohibitive or grapple with the inconvenience of systems that do not communicate seamlessly require both time and troubleshooting skills. However, solutions allow these systems to become better integrated and talk to one another and communicate with home dwellers via mobile devices or voice activation (i.e., IFTTT or digital virtual assistants from Apple and Google). With such a wide range of types of data collected, it highlights the unlimited possibilities and also the challenges resulting from the lack of a standard method of data collection in the IoT space.

The IoT technology space has rapidly evolved in recent years, with continued growth anticipated [87]. Many dedicated home-monitoring systems, explicitly designed for health, are not affordable, are negatively associated with declining health and stigma around ageing, and as such, individuals may opt-out of using these systems. IoT technology is trendy. It is designed for younger generations who have grown up immersed in technology. As technology has become more integrated into our lives, we can leverage these technologies, designed to improve comfort, convenience, improve safety, and monitoring in the home, as needed. While not necessarily designed with health in mind, these systems can monitor behaviours and provide insights into evolving patterns of behaviours that can point to changes in individual health. Moreover, if one lives in a smart home when the need arises, the existing technology can be activated to provide increased support and comfort.

This category of healthcare technology brings an entirely new layer of complexity due to risks associated with (potentially) personally identified data, health data, and individual privacy, rights, and ethical considerations [88]. Nevertheless, with careful implementation, there are positive outcomes possible from prevention to health promotion, health monitoring, all with the ultimate goal of reducing morbidity and mortality. Technology, when used appropriately, can improve quality of life, including physical, mental, and emotional/psychological health. These interventions can also focus on personal needs at the individual level, as well as at the population level.

Limitations:

As is the case with literature reviews, possible oversights of potentially relevant publications and relevant research in other languages may have occurred. We recognize that not all work is published in peer-reviewed journals, and the selected published articles are not automatically representative of all possible solutions. Additionally, due to the rapid progress in the field, the authors acknowledge that new insights may have emerged since the initial search and writing of this paper. Another potential limitation is the use of the term "smart home," which may have excluded relevant research set in a community or institution.

Future suggestions:

If we want to see these technologies used in the future to improve the health of vulnerable populations, including the ageing population, we must scale up our solutions and find ways to solve the interoperability and data quality issues. The Internet of Things ushers in a period of ultra-connectivity, converting regular sensors into vital data sources which, when linked to the cloud services, can manage big data with benefits for policymakers. We can thus leverage commercial, off-the-shelf instruments, like smart Wi-Fi thermostats and wearable devices to collect health indicators, integrate the data with new tools, and analyze and interpret it to benefit all.

Conclusion:

In conclusion, Internet of Things (IoT) smart home technology has the potential to improve the monitoring of vulnerable populations, especially those ageing in the community. This review suggests exploring alternative data sources to reinforce remote health monitoring using data from the IoT and other sensors. Despite some evidence, there is still a lack of large-scale utilization of these technologies for health. The proposed definition of smart homes for healthcare will enable the field to expand and invite new progress in remote patient monitoring in public health. The use of Big Data and artificial intelligence, including machine learning and deep learning analysis in real-time, will be the future of in-home health monitoring.

Acknowledgments:

The authors would like to thank Adson Rocha for the help in screening, charting, and providing input throughout the process. The Ubiquitous Health Technology Lab (UbiLab) volunteers, namely: Clarisse Misola, Nadia Somani, Arjun Mehta, Chaeyoon Jeong, Thianna Edwards, Kunal Karhanis, and Harneet Dhillon, for their timely help whenever and wherever required.

Funding:

The authors would like to thank the Natural Sciences and Energy Research Council (NSERC), ecobee, and MITACS for their support of this work.

Declarations of interest:

The authors declare none.

Reference

1. Alam MR, Reaz MBI, Ali MAM. A Review of Smart Homes—Past, Present, and Future. IEEE Trans Syst Man, Cybern Part C (Applications Rev [Internet] 2012 Nov;42(6):1190–1203. [doi: 10.1109/TSMCC.2012.2189204]
2. Alaa M, Zaidan AA, Zaidan BB, Talal M, Kiah MLM. A review of smart home applications based on the Internet of Things. J Netw Comput Appl [Internet] 2017 Nov;97:48–65. [doi: 10.1016/j.jnca.2017.08.017]
3. Miskelly FG. Assistive technology in elderly care. Age Ageing [Internet] 2001 Nov 1 [cited 2019 Nov 28];30(6):455–458. [doi: 10.1093/ageing/30.6.455]
4. Alberdi Aramendi A, Weakley A, Aztiria Goenaga A, Schmitter-Edgecombe M, Cook DJ. Automatic assessment of functional health decline in older adults based on smart home data. J Biomed Inform [Internet] 2018 May [cited 2018 Aug 20];81:119–130. [doi: 10.1016/j.jbi.2018.03.009]
5. Mora N, Grossi F, Russo D, Barsocchi P, Hu R, Brunschwiler T, Michel B, Cocchi F, Montanari E, Nunziata S, Matrella G, Ciampolini P. IoT-based home monitoring:

Supporting practitioners' assessment by behavioural analysis. Sensors (Switzerland) [Internet] MDPI AG; 2019 Jul 2 [cited 2020 Sep 17];19(14). PMID:31340542
6. Amiribesheli M, Benmansour A, Bouchachia A. A review of smart homes in healthcare. J Ambient Intell Humaniz Comput [Internet] Springer Berlin Heidelberg; 2015 Aug 14 [cited 2018 Oct 23];6(4):495–517. [doi: 10.1007/s12652-015-0270-2]
7. Dasios A, Gavalas D, Pantziou G, Konstantopoulos C. Hands-On Experiences in Deploying Cost-Effective Ambient-Assisted Living Systems. Sensors [Internet] 2015 Jun 18;15(6):14487–14512. [doi: 10.3390/s150614487]
8. Tirado Herrero S, Nicholls L, Strengers Y. Smart home technologies in everyday life: do they address key energy challenges in households? Curr Opin Environ Sustain [Internet] 2018 Apr;31:65–70. [doi: 10.1016/j.cosust.2017.12.001]
9. Robles RJ, Kim T-H. A Review on Security in Smart Home Development. undefined 2010;
10. Miao Yu, Rhuma A, Naqvi SM, Liang Wang, Chambers J. A Posture Recognition-Based Fall Detection System for Monitoring an Elderly Person in a Smart Home Environment. IEEE Trans Inf Technol Biomed [Internet] 2012 Nov;16(6):1274–1286. [doi: 10.1109/TITB.2012.2214786]
11. Han J, Choi C, Park W, Lee I, Kim S. Smart home energy management system including renewable energy based on ZigBee and PLC. IEEE Trans Consum Electron [Internet] 2014 May;60(2):198–202. [doi: 10.1109/TCE.2014.6851994]
12. Kyung Chang Lee, Hong-Hee Lee. Network-based fire-detection system via controller area network for smart home automation. IEEE Trans Consum Electron [Internet] 2004 Nov;50(4):1093–1100. [doi: 10.1109/TCE.2004.1362504]
13. What Will Smart Homes Look Like in 10 Years? | Time [Internet]. [cited 2021 Oct 19]. Available from: https://time.com/5634791/smart-homes-future/
14. Sprint G, Cook DJ, Fritz R, Schmitter-Edgecombe M. Using Smart Homes to Detect and Analyze Health Events. Computer (Long Beach Calif) [Internet] 2016 Nov;49(11):29–37. [doi: 10.1109/MC.2016.338]
15. Gawrońska K, Lorkowski J. Smart homes for the older population: particularly important during the COVID-19 outbreak. Reumatologia [Internet] 2021;59(1):41–46. PMID:33707795
16. Arksey H, O'Malley L. Scoping studies: Towards a methodological framework. Int J Soc Res Methodol Theory Pract 2005 Feb;8(1):19–32. [doi: 10.1080/1364557032000119616]
17. Daudt HML, Van Mossel C, Scott SJ. Enhancing the scoping study methodology: A large, inter-professional team's experience with Arksey and O'Malley's framework. BMC Med Res Methodol. BioMed Central; 2013. p. 1–9. [doi: 10.1186/1471-2288-13-48]
18. Levac D, Colquhoun H, O'Brien KK. Scoping studies: Advancing the methodology. Implement Sci [Internet] BioMed Central; 2010 Sep 20 [cited 2020 Apr 21];5(1):69. PMID:20854677
19. Pham MT, Rajić A, Greig JD, Sargeant JM, Papadopoulos A, McEwen SA. A scoping review of scoping reviews: advancing the approach and enhancing the consistency. Res Synth Methods [Internet] John Wiley and Sons Ltd; 2014 Dec 1 [cited 2020 Apr 21];5(4):371–385. [doi: 10.1002/jrsm.1123]
20. Citation Guides | Mendeley [Internet]. [cited 2021 Nov 5]. Available from: https://www.mendeley.com/guides/citation-guides/
21. Zotero | Your personal research assistant [Internet]. [cited 2021 Nov 5]. Available from: https://www.zotero.org/
22. Bock C, Demiris G, Choi Y, Le T, Thompson HJ, Samuel A, Huang D. Engaging older adults in the visualization of sensor data facilitated by an open platform for connected devices.

Technol Health Care [Internet] 2016 Mar 11;24(4):541–50. PMID:27002473
23. Chen K-Y, Harniss M, Patel S, Johnson K. Implementing technology-based embedded assessment in the home and community life of individuals aging with disabilities: a participatory research and development study. Disabil Rehabil Assist Technol [Internet] 2014 Mar;9(2):112–20. PMID:23802128
24. Fritz RL, Dermody G. A nurse-driven method for developing artificial intelligence in “smart” homes for aging-in-place. Nurs Outlook [Internet] 2019 Mar;67(2):140–153. PMID:30551883
25. Skubic M, Alexander G, Popescu M, Rantz M, Keller J. A smart home application to eldercare: Current status and lessons learned. Technol Heal Care [Internet] IOS Press; 2009 Jan 1 [cited 2018 Nov 14];17(3):183–201. [doi: 10.3233/THC-2009-0551]
26. Dawadi PN, Cook DJ, Schmitter-Edgecombe M, Parsey C. Automated assessment of cognitive health using smart home technologies. Technol Heal Care [Internet] IOS Press; 2013 Aug 1 [cited 2018 Aug 20];21(4):323–343. PMID:23949177
27. Choi YK, Thompson HJ, Demiris G. Use of an internet-of-things smart home system for healthy aging in older adults in residential settings: Pilot feasibility study. JMIR Aging JMIR Publications Inc.; 2020 Jul 1;3(2). [doi: 10.2196/21964]
28. Clemente J, Li F, Valero M, Song W. Smart Seismic Sensing for Indoor Fall Detection, Location, and Notification. IEEE J Biomed Heal Informatics [Internet] 2020;24(2):524–532. [doi: 10.1109/JBHI.2019.2907498]
29. Pigini L, Bovi G, Panzarino C, Gower V, Ferratini M, Andreoni G, Sassi R, Rivolta MW, Ferrarin M. Pilot Test of a New Personal Health System Integrating Environmental and Wearable Sensors for Telemonitoring and Care of Elderly People at Home (SMARTA Project). Gerontology [Internet] 2017;63(3):281–286. PMID:28099965
30. Monteriù A, Prist MR, Frontoni E, Longhi S, Pietroni F, Casaccia S, Scalise L, Cenci A, Romeo L, Berta R, Pescosolido L, Orlandi G, Revel GM. A Smart Sensing Architecture for Domestic Monitoring: Methodological Approach and Experimental Validation. Sensors (Basel) [Internet] 2018 Jul 17 [cited 2018 Aug 20];18(7):2310. PMID:30018200
31. Grgurić A, Mošmondor M, Huljenić D. The smarthabits: An intelligent privacy-aware home care assistance system. Sensors (Switzerland) MDPI AG; 2019 Feb 2;19(4). PMID:30795587
32. Marcelino I, Laza R, Domingues P, Gómez-Meire S, Fdez-Riverola F, Pereira A. Active and assisted living ecosystem for the elderly. Sensors (Switzerland) [Internet] 2018 Apr 17 [cited 2018 Aug 20];18(4):1246. PMID:29673234
33. Yu J, An N, Hassan T, Kong Q. A Pilot Study on a Smart Home for Elders Based on Continuous In-Home Unobtrusive Monitoring Technology. HERD Heal Environ Res Des J [Internet] 2019 Jul 5;12(3):206–219. [doi: 10.1177/1937586719826059]
34. Kim J-YY, Liu N, Tan H-XX, Chu C-HH. Unobtrusive Monitoring to Detect Depression for Elderly with Chronic Illnesses. IEEE Sens J [Internet] 2017 Sep 1 [cited 2018 Aug 20];17(17):5694–5704. [doi: 10.1109/JSEN.2017.2729594]
35. Hassan MK, El Desouky AI, Elghamrawy SM, Sarhan AM. Intelligent hybrid remote patient-monitoring model with cloud-based framework for knowledge discovery. Comput Electr Eng [Internet] Pergamon; 2018 Aug 1 [cited 2018 Oct 31];70:1034–1048. [doi: 10.1016/J.COMPELECENG.2018.02.032]
36. Schlebusch T. Unobtrusive Health Screening on an Intelligent Toilet Seat. Acta Polytech [Internet] 2011 Jan 5 [cited 2018 Aug 21];51(5). [doi: 10.14311/1454]
37. Jung Y. Hybrid-aware model for senior wellness service in smart home. Sensors (Switzerland) [Internet] Multidisciplinary Digital Publishing Institute; 2017 May 22 [cited 2018 Oct 31];17(5):1182. [doi: 10.3390/s17051182]

38. Alsina-Pagès RM, Navarro J, Alías F, Hervás M. homeSound: Real-Time Audio Event Detection Based on High Performance Computing for Behaviour and Surveillance Remote Monitoring. Sensors 2017 Apr 13;17(4):854. PMID:28406459
39. Mahmoud S, Lotfi A, Langensiepen C. Behavioural pattern identification and prediction in intelligent environments. Appl Soft Comput [Internet] 2013 Apr [cited 2018 Aug 20];13(4):1813–1822. [doi: 10.1016/j.asoc.2012.12.012]
40. Cook DJ, Jakkula V. Anomaly Detection Using Temporal Data Mining in a Smart Home Environment. Methods Inf Med [Internet] 2008 [cited 2018 Oct 31]; PMID:18213431
41. Rashidi P, Cook DJ, Holder LB, Schmitter-Edgecombe M. Discovering activities to recognize and track in a smart environment. IEEE Trans Knowl Data Eng [Internet] 2011 Apr [cited 2018 Aug 20];23(4):527–539. PMID:21617742
42. Singla G, Cook DJ, Schmitter-Edgecombe M. Recognizing independent and joint activities among multiple residents in smart environments. J Ambient Intell Humaniz Comput [Internet] Springer-Verlag; 2010 Mar 1 [cited 2018 Aug 20];1(1):57–63. [doi: 10.1007/s12652-009-0007-1]
43. Damodaran N, Haruni E, Kokhkharova M, Schäfer J. Device free human activity and fall recognition using WiFi channel state information (CSI). CCF Trans Pervasive Comput Interact [Internet] 2020 Mar 30;2(1):1–17. [doi: 10.1007/s42486-020-00027-1]
44. Hamad RA, Hidalgo AS, Bouguelia MR, Estevez ME, Quero JM. Efficient Activity Recognition in Smart Homes Using Delayed Fuzzy Temporal Windows on Binary Sensors. IEEE J Biomed Heal Informatics Institute of Electrical and Electronics Engineers Inc.; 2020 Feb 1;24(2):387–395. PMID:31135373
45. Enshaeifar S, Zoha A, Markides A, Skillman S, Acton ST, Elsaleh T, Hassanpour M, Ahrabian A, Kenny M, Klein S, Rostill H, Nilforooshan R, Barnaghi P. Health management and pattern analysis of daily living activities of people with dementia using in-home sensors and machine learning techniques. PLoS One [Internet] 2018;13(5). [doi: 10.1371/journal.pone.0195605]
46. Ros M, Cuéllar MP, Delgado M, Vila A. Online recognition of human activities and adaptation to habit changes by means of learning automata and fuzzy temporal windows. Inf Sci (Ny) [Internet] 2013 Jan [cited 2018 Aug 20];220:86–101. [doi: 10.1016/j.ins.2011.10.005]
47. Navarro J, Vidaña-Vila E, Alsina-Pagès R, Hervás M, Navarro J, Vidaña-Vila E, Alsina-Pagès RM, Hervás M. Real-Time Distributed Architecture for Remote Acoustic Elderly Monitoring in Residential-Scale Ambient Assisted Living Scenarios. Sensors [Internet] Multidisciplinary Digital Publishing Institute; 2018 Aug 1 [cited 2018 Nov 13];18(8):2492. [doi: 10.3390/s18082492]
48. Gayathri KS, Easwarakumar KS, Elias S. Fuzzy ontology based activity recognition for assistive health care using smart home. Int J Intell Inf Technol [Internet] 2020;16(1):17–31. [doi: 10.4018/IJIIT.2020010102]
49. Kwon O, Shim JM, Lim G. Single activity sensor-based ensemble analysis for health monitoring of solitary elderly people. Expert Syst Appl [Internet] Pergamon; 2012 Apr 1 [cited 2018 Nov 13];39(5):5774–5783. [doi: 10.1016/j.eswa.2011.11.090]
50. Taiwo O, Ezugwu AE. Smart healthcare support for remote patient monitoring during covid-19 quarantine. Informatics Med unlocked 2020;20:100428. PMID:32953970
51. Bassoli M, Bianchi V, De Munari I, Ciampolini P. An IoT approach for an AAL Wi-Fi-based monitoring system. IEEE Trans Instrum Meas 2017; [doi: 10.1109/TIM.2017.2753458]
52. Virone G, Alwan M, Dalal S, Kell SW, Turner B, Stankovic JA, Felder R. Behavioral Patterns of Older Adults in Assisted Living. IEEE Trans Inf Technol Biomed [Internet] 2008 May [cited 2018 Aug 20];12(3):387–398. [doi: 10.1109/TITB.2007.904157]

53. Lazarou I, Karakostas A, Stavropoulos TG, Tsompanidis T, Meditskos G, Kompatsiaris I, Tsolaki M. A Novel and Intelligent Home Monitoring System for Care Support of Elders with Cognitive Impairment. J Alzheimer's Dis [Internet] 2016 Oct 18 [cited 2018 Aug 20];54(4):1561–1591. PMID:27636843
54. Hercog D, Sedonja D, Recek B, Truntič M, Gergič B. Smart home solutions using Wi-Fi-based hardware. Teh Vjesn [Internet] 2020;27(4):1351–1358. [doi: 10.17559/TV-20190730075217]
55. Yang C-C, Hsu Y-L. Remote monitoring and assessment of daily activities in the home environment. J Clin Gerontol Geriatr [Internet] 2012 Sep [cited 2018 Aug 20];3(3):97–104. [doi: 10.1016/j.jcgg.2012.06.002]
56. Yao L, Sheng QZ, Benatallah B, Dustdar S, Wang X, Shemshadi A, Kanhere SS. WITS: an IoT-endowed computational framework for activity recognition in personalized smart homes. Computing [Internet] Springer Vienna; 2018 Apr 6 [cited 2018 Aug 20];100(4):369–385. [doi: 10.1007/s00607-018-0603-z]
57. Fleury A, Vacher M, Noury N. SVM-based multimodal classification of activities of daily living in health smart homes: Sensors, algorithms, and first experimental results. IEEE Trans Inf Technol Biomed [Internet] 2010 Mar [cited 2018 Aug 20];14(2):274–283. PMID:20007037
58. Fiorini L, Cavallo F, Dario P, Eavis A, Caleb-Solly P. Unsupervised Machine Learning for Developing Personalised Behaviour Models Using Activity Data. Sensors [Internet] 2017 May 4 [cited 2018 Aug 20];17(5):1034. PMID:28471405
59. Fritz RL, Wilson M, Dermody G, Schmitter-Edgecombe M, Cook DJ. Automated smart home assessment to support pain management: multiple methods analysis. J Med Internet Res JMIR Publications Inc.; 2020 Nov 1;22(11). PMID:33105099
60. Austin J, Dodge HH, Riley T, Jacobs PG, Thielke S, Kaye J. A Smart-Home System to Unobtrusively and Continuously Assess Loneliness in Older Adults. IEEE J Transl Eng Heal Med [Internet] Institute of Electrical and Electronics Engineers; 2016 [cited 2018 Oct 23];4:2800311. PMID:27574577
61. Lyons BE, Austin D, Seelye A, Petersen J, Yeargers J, Riley T, Sharma N, Mattek N, Wild K, Dodge H, Kaye JA. Pervasive computing technologies to continuously assess Alzheimer's disease progression and intervention efficacy. Front Aging Neurosci 2015; PMID:26113819
62. Junnila S, Kailanto H, Merilahti J, Vainio AM, Vehkaoja A, Zakrzewski M, Hyttinen J. Wireless, multipurpose in-home health monitoring platform: Two case trials. IEEE Trans Inf Technol Biomed 2010; PMID:20007034
63. Lamprinakos GC, Asanin S, Broden T, Prestileo A, Fursse J, Papadopoulos KA, Kaklamani DI, Venieris IS. An integrated remote monitoring platform towards Telehealth and Telecare services interoperability. Inf Sci (Ny) [Internet] 2015 Jul [cited 2018 Aug 20];308:23–37. [doi: 10.1016/j.ins.2015.02.032]
64. Cahill J, Portales R, McLoughin S, Nagan N, Henrichs B, Wetherall S. IoT/Sensor-Based Infrastructures Promoting a Sense of Home, Independent Living, Comfort and Wellness. Sensors [Internet] 2019 Jan 24;19(3):485. PMID:30682864
65. Mora N, Matrella G, Ciampolini P, Mora N, Matrella G, Ciampolini P. Cloud-based behavioral monitoring in smart homes. Sensors (Switzerland) [Internet] Multidisciplinary Digital Publishing Institute; 2018 Jun 15 [cited 2018 Aug 20];18(6):1951. PMID:29914127
66. Liu L, Stroulia E, Nikolaidis I, Miguel-Cruz A, Rios Rincon A. Smart homes and home health monitoring technologies for older adults: A systematic review. Int J Med Inform [Internet] 2016 Jul [cited 2018 Aug 20];91:44–59. [doi: 10.1016/j.ijmedinf.2016.04.007]

67. Moyle W, Murfield J, Lion K. The effectiveness of smart home technologies to support the health outcomes of community-dwelling older adults living with dementia: A scoping review. Int J Med Inform [Internet] 2021;153:104513. PMID:34116363
68. Husebo BS, Heintz HL, Berge LI, Owoyemi P, Rahman AT, Vahia I V. Sensing Technology to Monitor Behavioral and Psychological Symptoms and to Assess Treatment Response in People with Dementia. A Systematic Review. Front Pharmacol [Internet] 2019;10:1699. PMID:32116687
69. Chan JKY, Klainin-Yobas P, Chi Y, Gan JKE, Chow G, Wu XV. The effectiveness of e-interventions on fall, neuromuscular functions and quality of life in community-dwelling older adults: A systematic review and meta-analysis. Int J Nurs Stud [Internet] 2021 Jan;113:103784. PMID:33120138
70. Bossung V, Kast K. Smart sensors in pregnancy: Narrative review on the use of smart home technology in routine prenatal care. Z Evid Fortbild Qual Gesundhwes [Internet] 2021 Aug;164:35–43. PMID:34215532
71. Amiribesheli M, Benmansour A, Bouchachia A. A review of smart homes in healthcare. J Ambient Intell Humaniz Comput [Internet] 2015 Aug 14 [cited 2018 Aug 20];6(4):495–517. [doi: 10.1007/s12652-015-0270-2]
72. Wang J, Spicher N, Warnecke JM, Haghi M, Schwartze J, Deserno TM. Unobtrusive Health Monitoring in Private Spaces: The Smart Home. Sensors (Basel) [Internet] 2021 Jan 28;21(3). PMID:33525460
73. Marques G, Pitarma R, M. Garcia N, Pombo N. Internet of Things Architectures, Technologies, Applications, Challenges, and Future Directions for Enhanced Living Environments and Healthcare Systems: A Review. Electronics [Internet] 2019 Sep 24;8(10):1081. [doi: 10.3390/electronics8101081]
74. Cortés OL, Piñeros H, Aya PA, Sarmiento J, Arévalo I. Systematic review and meta-analysis of clinical trials: In–hospital use of sensors for prevention of falls. Medicine (Baltimore) [Internet] Wolters Kluwer Health; 2021 [cited 2021 Nov 5];100(41). [doi: 10.1097/MD.0000000000027467]
75. Marikyan D, Papagiannidis S, Alamanos E. A systematic review of the smart home literature: A user perspective. Technol Forecast Soc Change [Internet] 2019 Jan;138:139–154. [doi: 10.1016/j.techfore.2018.08.015]
76. Santosa A, Wall S, Fottrel E, Högberg U, Byass P. The development and experience of epidemiological transition theory over four decades: A systematic review. Glob Health Action Co-Action Publishing; 2014;7(SUPP.1). [doi: 10.3402/gha.v7.23574]
77. Defo BK. Demographic, epidemiological, and health transitions: Are they relevant to population health patterns in Africa? Glob Health Action Co-Action Publishing; 2014;7(SUPP.1). [doi: 10.3402/gha.v7.22443]
78. Dyson T. Population and Development: The Demographic Transition. [Internet]. Prog Dev Stud. Zed; 2010 [cited 2019 Sep 3]. [doi: 10.1177/146499341001100307]ISBN:9781842779590
79. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science (80-) [Internet] 2019 Oct 25;366(6464):447–453. [doi: 10.1126/science.aax2342]
80. Buolamwini J, Gebru T. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification [Internet]. Proc Mach Learn Res. PMLR; 2018 [cited 2021 Nov 16]. p. 77–91. Available from: https://proceedings.mlr.press/v81/buolamwini18a.html
81. Goodman A, Fleming K, Markwick N, Morrison T, Lagimodiere L, Kerr T. “They treated me like crap and I know it was because I was Native”: The healthcare experiences of

Aboriginal peoples living in Vancouver's inner city. Soc Sci Med [Internet] 2017 Apr;178:87–94. [doi: 10.1016/j.socscimed.2017.01.053]

82. Nguyen NH, Subhan FB, Williams K, Chan CB. Barriers and Mitigating Strategies to Healthcare Access in Indigenous Communities of Canada: A Narrative Review. Healthcare [Internet] 2020 Apr 26;8(2):112. [doi: 10.3390/healthcare8020112]
83. Phillips-Beck W, Eni R, Lavoie JG, Avery Kinew K, Kyoon Achan G, Katz A. Confronting Racism within the Canadian Healthcare System: Systemic Exclusion of First Nations from Quality and Consistent Care. Int J Environ Res Public Health [Internet] 2020 Nov 11;17(22):8343. [doi: 10.3390/ijerph17228343]
84. Holdcroft A. Gender bias in research: how does it affect evidence based medicine? J R Soc Med [Internet] 2007 Jan;100(1):2–3. PMID:17197669
85. Why are males still the default subjects in medical research? [Internet]. [cited 2021 Nov 16]. Available from: https://theconversation.com/why-are-males-still-the-default-subjects-in-medical-research-167545
86. Mihailidis A, Boger J, Hoey J, Jiancaro T. Zero Effort Technologies: Considerations, Challenges, and Use in Health, Wellness, and Rehabilitation [Internet]. Synth Lect Assist Rehabil Heal Technol. Morgan & Claypool Publishers; 2011 Aug. [doi: 10.2200/S00380ED1V01Y201108ARH002]
87. Statista. IoT market size worldwide 2017-2025 [Internet]. 2021 [cited 2021 Nov 16]. Available from: https://www.statista.com/statistics/976313/global-iot-market-size/
88. Guhr N, Werth O, Blacha PPH, Breitner MH. Privacy concerns in the smart home context. SN Appl Sci [Internet] 2020 Feb 21;2(2):247. [doi: 10.1007/s42452-020-2025-8]

Supplementary Table-1

Search strategy in details

Database	Number of Articles	Query
PubMed	549	((((((((("smart home" AND Health* AND monitor*)))))) OR ((((((AAL AND Health* AND monitor*))))))) OR (((((("ambient assisted living" AND Health* AND monitor*)))))) OR (((((("active assisted living" AND Health* AND monitor*)))))
Science Direct	1,721	("smart home*" AND health* AND monitor*) OR (AAL AND health* AND monitor*) OR ("ambient assisted living" AND Health* AND monitor*) OR ("active assisted living" AND health*)
Scopus	3649	Total
	509	"Smart home" health* monitor*
	538	AAL AND health* AND monitor
	2573	"ambient assisted living" AND Health* AND monitor*
	29	"active assisted living" AND Health* AND monitor*
CINAHL	76	Total
	13	"Smart home" health* monitor*
	2	AAL AND health* AND monitor
	6	"ambient assisted living" AND Health* AND monitor*
	55	"active assisted living" AND Health* AND monitor*
All database	**5995**	

Note: Label: behavio*, individual, population
Not limited to: geographic location
Limiters: English, human, 2007-2020

Exclude: Not English
Include: research articles, review articles
Searched on Aug 22, 2021, at 10:00 am

Supplementary Table-2

Domain and Journal of publication of the selected articles

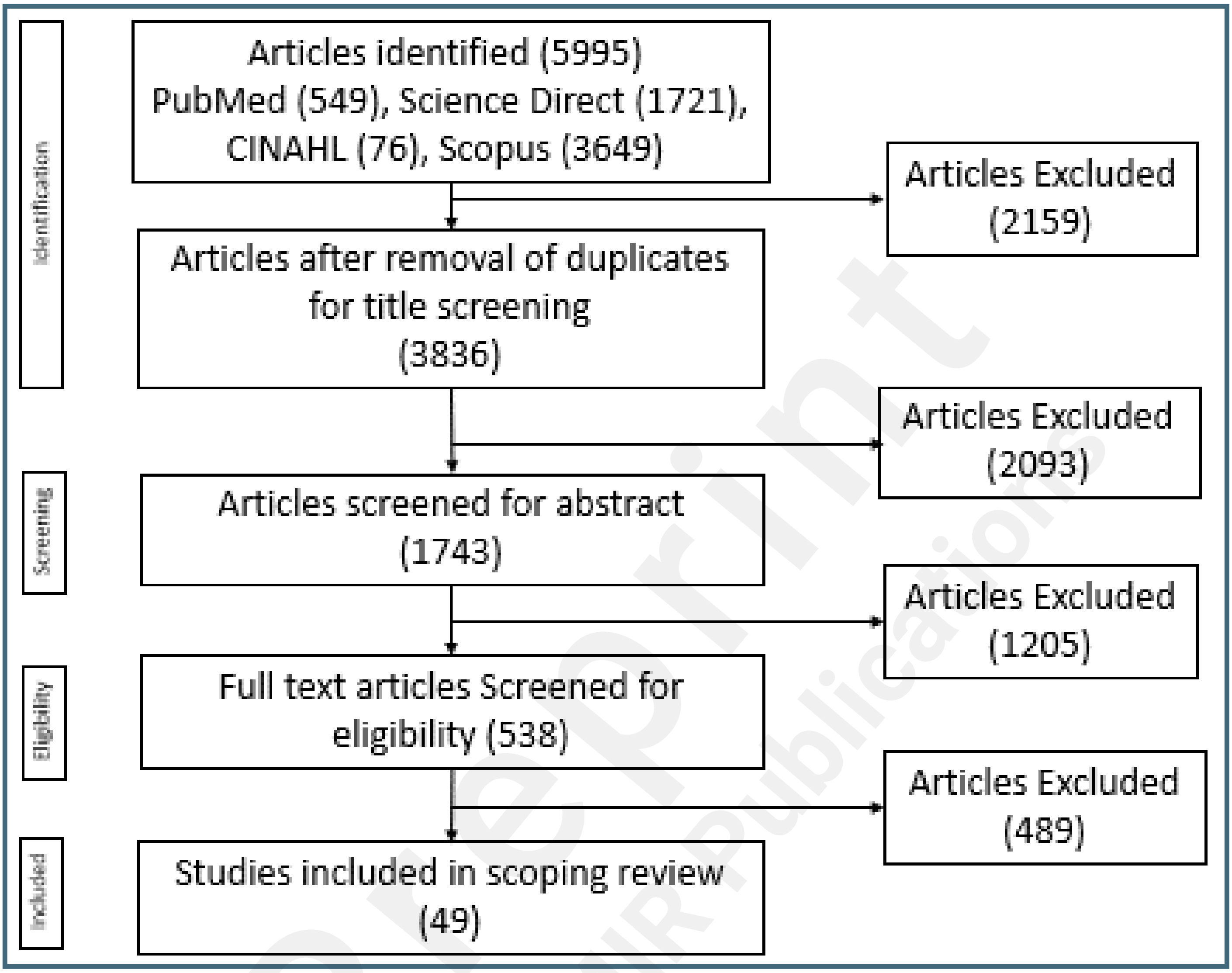
Domain	**Name of Journal**	**Number of Publications**
Engineering	Sensors (Switzerland)	7
Engineering	Sensors	5
IEEE Group of journals	Transactions on Information Technology in Biomedicine	3
IEEE Group of journals	Journal of Biomedical and Health Informatics	2
Engineering	Acta Polytechnica	1
Engineering	Applied Soft Computing Journal	1
Engineering	CCF Transactions on Pervasive Computing and Interaction	1
Engineering	Computer	1
Engineering	Computers & Electrical Engineering	1
Engineering	Computing	1
Engineering	Expert Systems with Applications	1
Engineering	International Journal of Intelligent Information Technologies	1
Engineering	Journal of Ambient Intelligence and Humanized Computing	1
Engineering	Tehnicki Vjesnik	1
IEEE Group of journals	Journal of Translational Engineering in Health and Medicine	1
IEEE Group of journals	Sensors Journal	1
IEEE Group of journals	Transactions on Instrumentation and Measurement	1
IEEE Group of journals	Transactions on Knowledge and Data Engineering	1
Health informatics	Technology and Health Care	3
Health informatics	Information Sciences	2
Health informatics	Informatics in medicine unlocked	1
Health informatics	Journal of Biomedical Informatics	1
Health informatics	Journal of Medical Internet Research	1
Health informatics	Methods of Information in Medicine	1
Health	Disability and Rehabilitation: Assistive Technology	1
Health	Frontiers in Aging Neuroscience	1
Health	Gerontology	1

Health	Health Environments Research and Design Journal	1
Health	JMIR ageing	1
Health	Journal of Alzheimer's Disease	1
Health	Journal of Clinical Gerontology and Geriatrics	1
Health	Nursing Outlook	1
Health	PLoS ONE	1

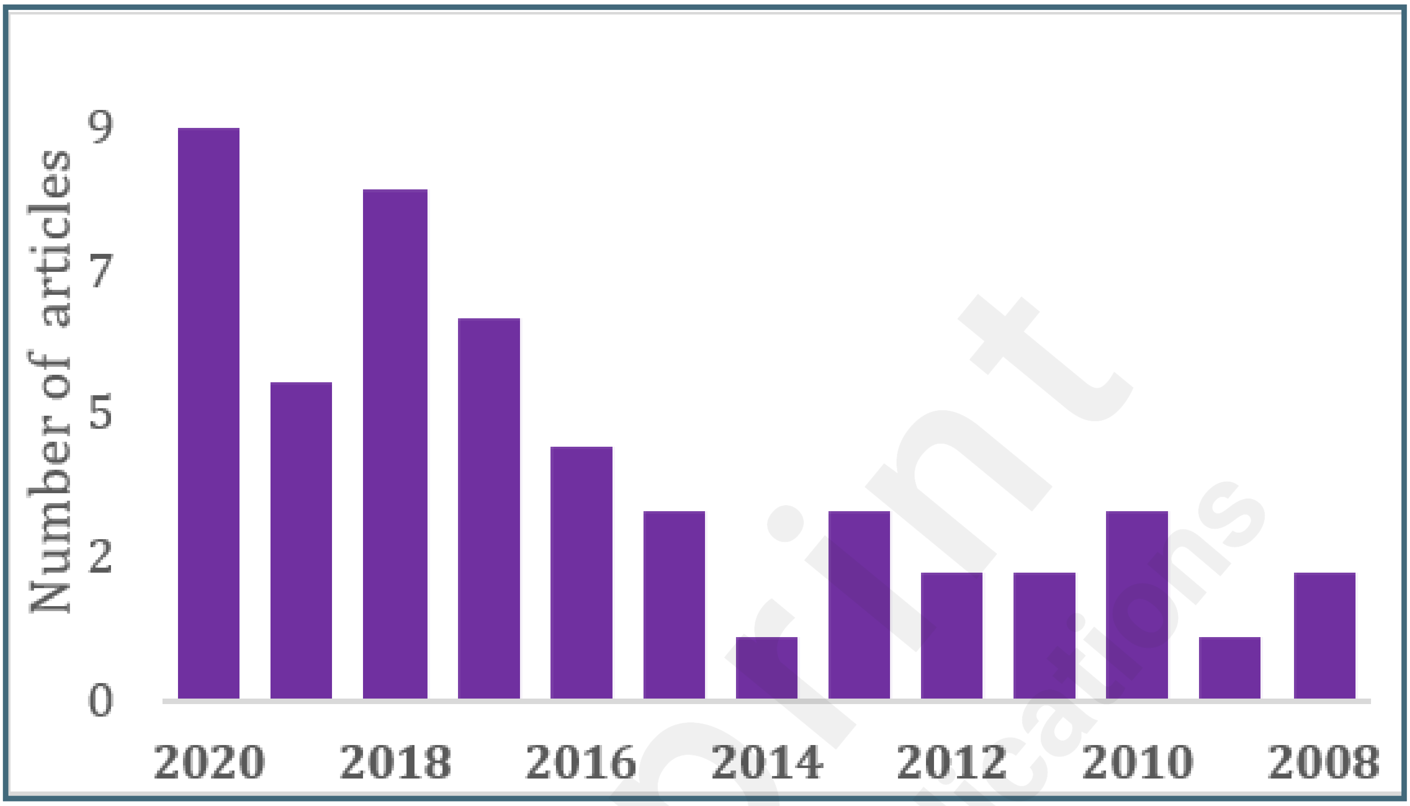
Supplementary Files

Figures

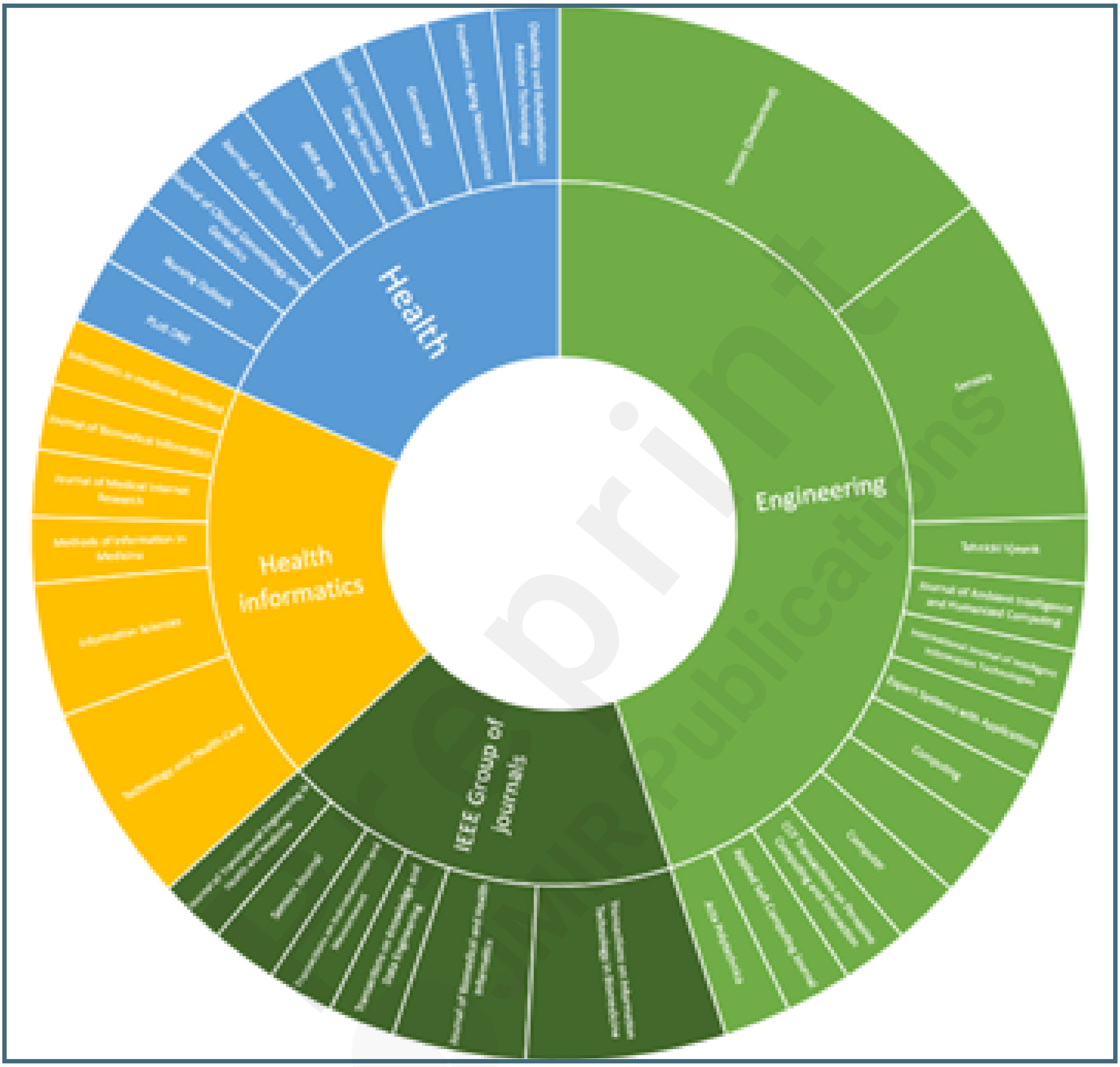
PRISMA Flow Chart - Systematic Study Selection.



Articles by year of publication.



Journals of publication.



Word cloud of article keywords.