RESEARCH ARTICLE

Scoping Review of Healthcare Literature on Mobile, Wearable, and Textile Sensing Technology for Continuous Monitoring

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Abstract

Remote monitoring of health can reduce frequent hospitalisations, diminishing the burden on the healthcare system and cost to the community. Patient monitoring helps identify symptoms associated with diseases or disease-driven disorders, which makes it an essential element of medical diagnoses, clinical interventions, and rehabilitation treatments for severe medical conditions. This monitoring can be expensive and time-consuming and provide an incomplete picture of the state of the patient. In the last decade, there has been a significant increase in the adoption of mobile and wearable devices, along with the introduction of smart textile solutions that offer the possibility of continuous monitoring. These alternatives fuel a technology shift in healthcare, one that involves the continuous tracking and monitoring of individuals. This scoping review examines how mobile, wearable, and textile sensing technology have been permeating healthcare by offering alternate solutions to challenging issues, such as personalised prescriptions or home-based secondary prevention. To do so, we have selected 222 healthcare literature articles published from 2007 to 2019 and reviewed them following the PRISMA process under the schema of a scoping review framework. Overall, our findings show a recent increase in research on mobile sensing technology to address patient monitoring, reflected by 128 articles published in journals and 19 articles in conference proceedings between 2014 and 2019, which represents 57.65% and 8.55% respectively of all included articles.

Keywords Smartphones · Wearable devices · Textile technology · Continuous sensing · Remote monitoring

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1 Introduction

In the last decades, we have experienced different challenges derived from global epidemics (e.g. H1N1 [1], Ebola [2], measles [3], dengue fever [4]) that had shifted our political, economic, and healthcare systems. Recently, the fatalities derived from the pandemic of the coronavirus disease (COVID-19)[1] are rising, and with it, a concomitant increase in the demand of healthcare causing care services to become insufficient. The structure of our healthcare system relies on a centralised hospitalisation, in which ill citizens travel to the clinic to receive a medical diagnosis. While this model has been effective in the past, we are now witnessing a shift in political, economic, and healthcare models, in which the efforts to conserve dwindling resources lie towards using remote technology to address medical care service locally in neighbourhoods and individual homes.

Empowering citizens and patients with technology to enable self-care and remote monitoring can help reduce health expenditures by minimising the number of visits to clinics and hospitals. In the scope of ubiquitous computing research, helping patients to self-manage and remote monitoring aim at providing low-cost everyday home usage due to the advances in sensor, communication, and portable technology. For this paper, we consider mobile, wearable, and textile (MWT) sensing technology and the use of these devices to monitor physical and social behaviour, either individually or collectively. A mobile device may consist of gadgets such as smartphones and tablets [5]. Wearables can offer a discreet and convenient approach to gathering data; some examples of items include watches, fitness trackers, badges, glasses, and similar devices [6]. Textiles are defined as smart if they have intrinsic properties that can respond to the environment and to a user's stimuli. In contrast to currently available technology, they tend to be soft and adopted to smart ensemble garments [7]. These approaches help to improve the user experience by requiring low or no cognitive effort to operate in daily life (a.k.a. naturalistic conditions).

MWT sensing technology makes it possible to monitor a patient's health both long-term and continuously [8, 9]. Traditional methods of monitoring have frequently relied on admission to hospitals and nursing homes, which can be expensive and often inconvenient to patients.[2,,3] In this regard, technology and scientific progress aim at supporting early detection of disease, independent living, enhancing rehabilitation treatment, and assessment of wellbeing. There have been a few systematic reviews in this area. One review focused specifically on sensor-based authentication strategies to maintain patient privacy when using mHealth [10]. A 2018 review [11] of empirical health and wellbeing research on smartphone-based passive sensors identified a variety of limitations in terms of data sharing with participants, weak study designs, limited clinical integration, and privacy concerns.

This paper examines how a broader range of MWT technologies have been permeating the medical field by bringing technological solutions to problems in which continuous monitoring and personalised prescription are critical.

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[1] https://www.who.int/health-topics/coronavirus
[2] https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthcaresystem/bulletins/ukhealthaccounts/2015
[3] https://www.nhs.uk/conditions/coronavirus-covid-19/self-isolation-advice/

Moreover, we present a discussion to illustrate the technological tendencies and challenges. The literature analysis is framed based on the following research questions:

- How is mobile sensing technology being adopted into healthcare research?
- What types of health problems are the focus of MWT sensing technology?
- What is the current status of MWT sensing technologies regarding monitoring platforms or technologies, and how might this affect healthcare trends?

2 Methodology

The methodology and eligibility criteria were established a priori. The study was conducted as a scoping review, an approach intended to provide an overview of a diverse body of literature pertaining to a broad topic, as well as a descriptive overview of the reviewed material [12]. This scoping review conducts and reports according to the systematic reviews and meta-analysis (PRISMA) statements [13].

2.1 Eligibility Criteria

Original studies that discussed the use of MWT technology in healthcare were eligible for inclusion. The publications were restricted to journals and conference proceedings written in the English language.

Studies were excluded for two main reasons: (1) multiple articles reported on the same study and (2) studies did not evaluate the MWT technology.

2.2 Information Sources and Search Strategy

The published works were identified by conducting a systematic literature search through PubMed, which is a free electronic database of citations and abstracts comprised of over 28 million citations for biomedical articles from MEDLINE, life science journals, and online books. It is maintained by the National Center for Biotechnology Information (NCBI) at the National Library of Medicine (NLM). PubMed was used as a resource to concentrate relevant publications aiming to explore the different approaches to cope with medical challenges using MWT technologies and scientific advances. We used the MeSH (Medical Subject Headings) descriptors in order to analyse the literature corpus and bibliometric indicators. MeSH is the NLM-controlled vocabulary thesaurus used for indexing articles for PubMed,

The literature search was supplemented by a manual search of the reference lists of the retrieved articles related to physiological monitoring and wearable and mobile technology. The literature search was conducted using the following MeSH terms: ("Monitoring, Physiologic"[MeSH TERMS]) AND ("Wearable Electronic Devices"[MeSH TERMS] OR "Computers, Handheld"[MeSH TERMS]) and covered a period from 2007 (inclusive) to 2019 (inclusive) due to the introduction of sensor-equipped smartphones in 2007 (i.e. the first iPhone). The last literature search update was conducted on March 25th, 2020.

2.3 Study Selection

A PRISMA diagram for the study is provided in Fig. 1, which presents the flow diagram of the scoping review. Selection criteria consisted of articles that describe the used technology in the context of health-related MWT sensing technology. This included articles with any of the following specifications:

- Signal processing of data gathered with mobile sensors in a medical context.
- Hardware and software prototyping for monitoring purposes.
- System/app developments that facilitate the self-reporting of medical conditions/symptoms.
- Mental medical conditions as derived from health problems.

All identified titles ($n = 487$) were labelled as relevant, irrelevant, and unclear and were further discussed with the consensus of two researchers (JM, NH). The abstract of pre-selected works ($n = 394$) was screened for eligibility by three researchers (JM, LC, NH), and internal consistency was reliable (Cronbach's alpha $= 0.869$). The relevant articles ($n = 288$) were retrieved, and the entire texts were independently checked by
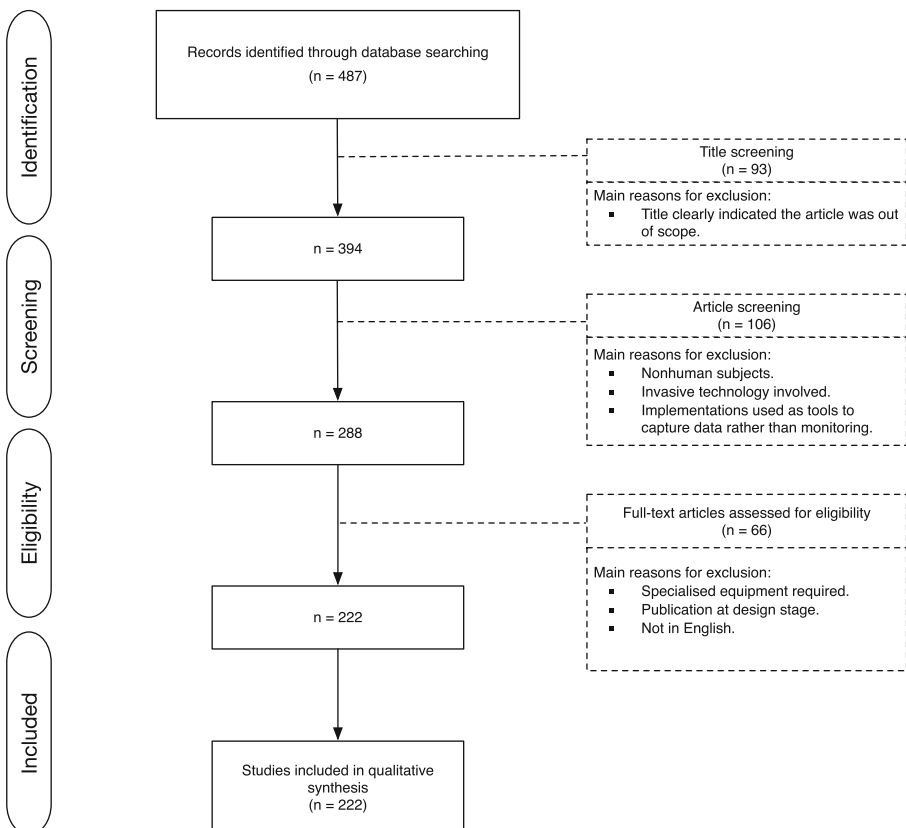

Fig. 1 Flow diagram for the literature search based on the protocol PRISMA.

three researchers (LC, JM, NH) to assure that the eligibility criteria were satisfied. Through this process, a total of 222 articles were included in the review.

To better understand how engineering approaches have permeated the medical field, we focused on the area of continuous health monitoring. We classified journals in three categories: medical-oriented, representing journals with primarily medical/clinician authors; engineering-focused health journals; and interdisciplinary, representing those journals focused on healthcare from an engineering perspective.

The included studies were reviewed by three of the authors who extracted relevant information from each article including country of origin of the authors/institutions, PubMed article category, type of technology used for sensing (smartphone, wearable, smart textile), type of sensing approach (opportunistic/participatory), type of sensor, location of the sensor, evaluation control, and health condition. Any disagreements were resolved through a discussion among four authors (JF, JM, LC, NH).

3 Results

This section presents findings regarding bibliometric analysis (3.1), data analysis towards measuring the maturity of the studies retrieved (3.2), mobile technology (3.3), sensing approach (3.4), sensing technology (3.5), and application in the healthcare field (3.6).

3.1 Bibliometric Analysis

In this era of ubiquitous technology and artificial intelligence (AI), the impact of engineering in medicine is increasing. Such collaboration benefits clinicians and enhances the patients' recovery experience, for instance, by personalising medication [14], enabling early diagnosis [15] and treatment of disease [16], and facilitating remote rehabilitation tasks [17], among others. These ground-breaking outcomes are possible through the contributions of multidisciplinary teams between clinicians and engineers.

In this cohort of articles, we can observe that the manuscripts reviewed are published in 85 journals, and according to PubMed, 40.09% are technology-oriented research. PubMed classifies them into nine main groups: informatics ($n = 52$), technology ($n = 23$), medicine ($n = 20$), health services ($n = 18$), sports medicine ($n = 16$), biotechnology ($n = 14$), health services ($n = 14$), cardiology ($n = 13$), and physiology ($n = 12$).

In Fig. 2, we observe that 45.49% of the articles ($n = 101$) derived from the medical-oriented journals have explored the adoption of mobile sensing as a healthcare monitoring technique. Some of the approaches target way to evaluate patients' acceptance of wearable/mobile technology, accuracy compared to golden standard equipment, and offer open challenges to the engineering community. Also, Fig. 2 shows that the engineering community ($n = 20$; 9.00%) altogether with the multidisciplinary effort ($n = 101$; 45.49%) account for 54.50% ($n = 121$) of work related to continuous healthcare monitoring. The latter includes technological prototype design, algorithm evaluation, and platform design. In general, 113 (50.90%) of the articles were published in the last few years (i.e. 2015–2019), depicting the increasing interest in the area.

When analysing the selected articles, one can observe the influence of specific countries by quantifying the number of publications, which is relevant due to the role
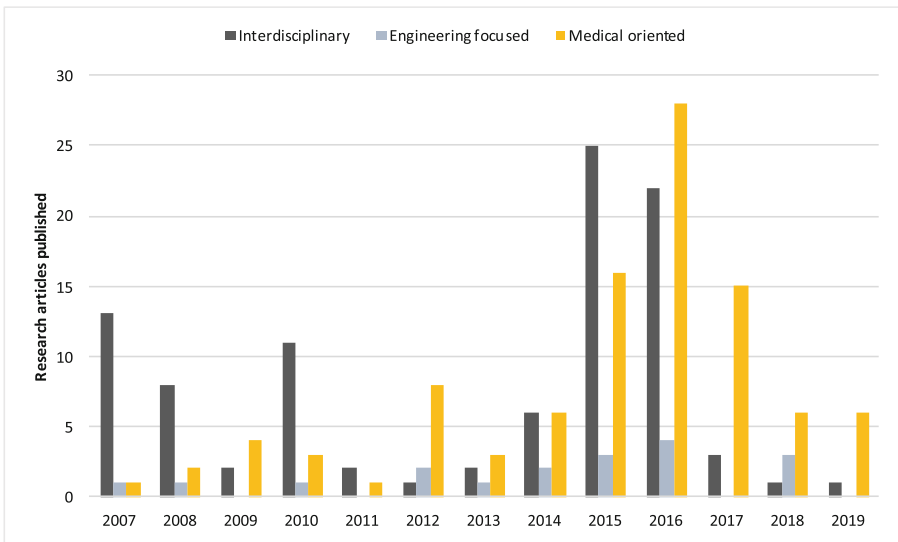
Fig. 2 The number of research articles published in scientific journals. Journals are grouped within three categories: medical-oriented, engineering-focused, and interdisciplinary, involving both the research areas.

taken by the different countries' institutions conducting economic analyses of regulations on medical devices (e.g. Food and Drug Administration in the USA,[4] Medicines & Healthcare products Regulatory Agency in the UK,[5] European Medicines Agency in the EU,[6] and National Medical Products Administration in China[7]). Such analysis includes the cost-benefit assessment of new medication, treatment techniques, diagnosis devices, and the impact on each country's economy,[8] which are decisions that have a paramount role in the manufacture manage care decision-maker [18], and research [19, 20].

In Fig. 3, we show the number of articles classified per country. Each publication has an average of five authors, accounting for 926 authors from 34 countries. In this regard, more than 2/3 of the articles originate from five countries. The USA ranked at the top, with approximately 25% of authorship as depicted in Fig. 3. Eligible articles included institutions mainly from sixteen countries (USA, UK, Korea, Australia, Germany, Netherlands, Canada, China, Spain, Japan, Italy, Singapore, Finland, France, Ireland, and Norway) that are leading research on users of constant monitoring technologies, which represents the 80.63% of all articles retrieved in this study.

3.2 Dissemination Style

While journal publications involve a robust peer-reviewed process that ensures reliability, conference proceedings consist of scholarly work and discussions, which can have a more flexible review process [21].

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[4] https://www.fda.gov/about-fda
[5] https://www.gov.uk/government/news/welcome-to-our-new-mhra-website
[6] https://www.ema.europa.eu/en
[7] http://english.nmpa.gov.cn/
[8] https://www.fda.gov/about-fda/reports/economic-impact-analyses-fda-regulations
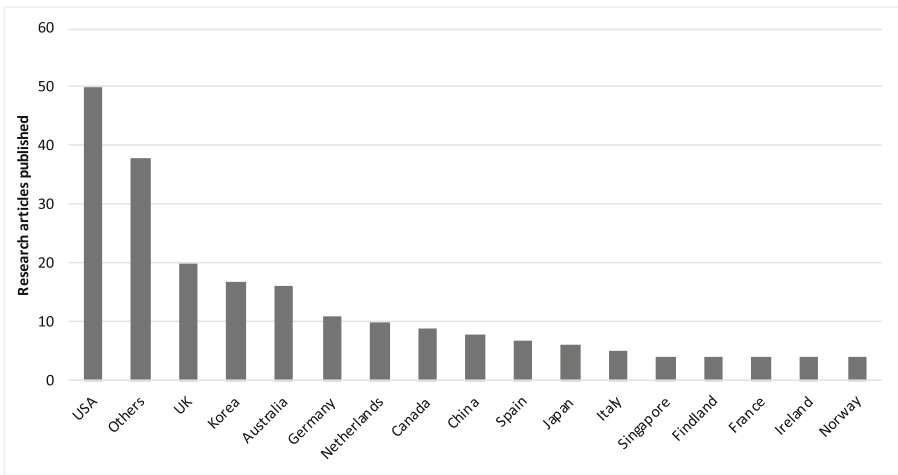
Fig. 3 The number of research articles grouped by the country where the authors' institutions are based.

Considering the publication type as a criterion of reliability illustrates how mobile sensing research is maturing. In Fig. 4, we observe that since 2014 there has been a significant increase in the number of journal articles published when compared to conference proceeding articles, the number of which has remained mostly constant. Of the research articles reviewed, 78.82% are from journals and less than 21.17% are from conference proceedings.

Table 1 shows the number of articles published according to their orientation (i.e. medical, engineering, or interdisciplinary). Nearly half of the journal articles published are in medical journals (45.49%), 57.65% of which have been available since 2014.
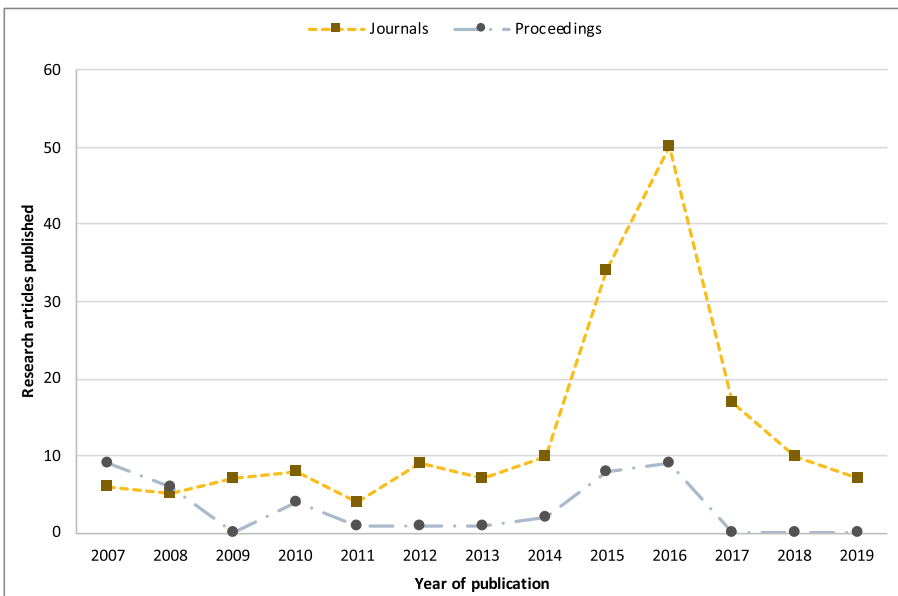

Fig. 4 The number of articles grouped by publication type: journals and conference proceedings.

Also, 12.76% of the conference proceedings articles published focused on engineering, while 87.23% of the proceedings come from interdisciplinary collaborations. This difference provides not only evidence of the interest from the engineering community in addressing some of the medical challenges but the acceptability from the medical community in adopting such approaches. This last statement can be appreciated as all the articles from the medical orientation build upon journal publication type.

Another approach to measuring how mobile sensing has been consolidated might be by identifying quantitative and qualitative research. Qualitative research is exploratory, and it helps to develop hypotheses for quantitative research. Quantitative research can provide broad insights resulting in a recommended course of action [22]. According to the data collected in this scoping review, 13.51% of projects adopt a randomised controlled trial (RCT), which is a quantitative research method known as the gold standard for the healthcare sector in the medical field (Table 2).

Figure 5 depicts the increase on RCT studies since 2014, which shows an increase in the strength of evidence gathered using this MWT technology, and the ratio in the last 2 years (i.e. 2018, 2019).

3.3 Research in Mobile, Wearable, and Textile Sensing Technology

Here we found that the use of smartphones and tablets leads portable technology given its high power and storage capabilities. Smartphones and tablets are followed by wearable gadgets such as fitness trackers and watches that, due to their unobtrusiveness and their continuing connection to the skin, become a convenient choice for the user and a strategic source of data for the researcher. Textiles open new research opportunities, given their distinguishing characteristic of integrating electronics into the manufacturing process. Out of 222 articles, 171 (77.02%) involved the use of smartphones, 94 (42.34%) focused on computer-related technology such as wearables, and 11 (4.95%) built on textile and fabric sensing approaches. Figure 6 shows the number of articles published in the last few years, which implies that mobile devices have been a feasible technology for the continuous monitoring of users' health.

3.4 Sensing Approaches

In the context of sensing approaches within mobile computing, intrusiveness refers to the undesirable and physical or psychological prominence of a device that interrupts a user's day-to-day activities [53]. Figure 7a illustrates mobile devices as tools to capture data (i.e. a participatory approach) manually and are increasingly being used as non-

Table 1 Publication type grouped within three categories: medical-oriented, engineering-focused, and interdisciplinary involving both types of research areas, as mentioned earlier.

	Journal	Proceedings
Interdisciplinary	60	41
Engineering focused	14	6
Medical oriented	101	0

Table 2 List of articles adopting RCT has a mechanism of validation.

Year	Publication
2007	–
2008	[23]
2014	[24, 25]
2015	[26]
2016	[27–33]
2017	[34–46]
2018	[47–50]
2019	[51, 52]

intrusive and automatic mechanisms for collecting data (i.e. an opportunistic approach). Findings show in Fig. 7a that 42.56% of studies collected data opportunistically [54–67] when utilising mobile devices. In contrast, Fig. 7b shows that wearable devices have mostly relied on sensing data opportunistically ($n = 86$, 90.52%), so that users' day-to-day activities are not interrupted. Except for 2007 and 2012, non-intrusive techniques have dominated the monitoring approach used. Overall, 70.37% of projects across mobile and wearable technology collected information opportunistically. The lack of participatory projects observed within the gap between 2012 and 2017 suggests that the advances in wearable technology are relevant to research monitoring technique (see Table 3 for details).

Figure 8 groups' devices are based on two general body areas: the upper body where devices are worn/carried, such as glasses, necklaces, and watches, and the lower body where devices are worn/carried on the waist, in a pocket, on the ankle, and in/on the shoes. This scoping review shows that there are three times as many articles about wearable technology than articles about mobile devices that are positioned on the chest/
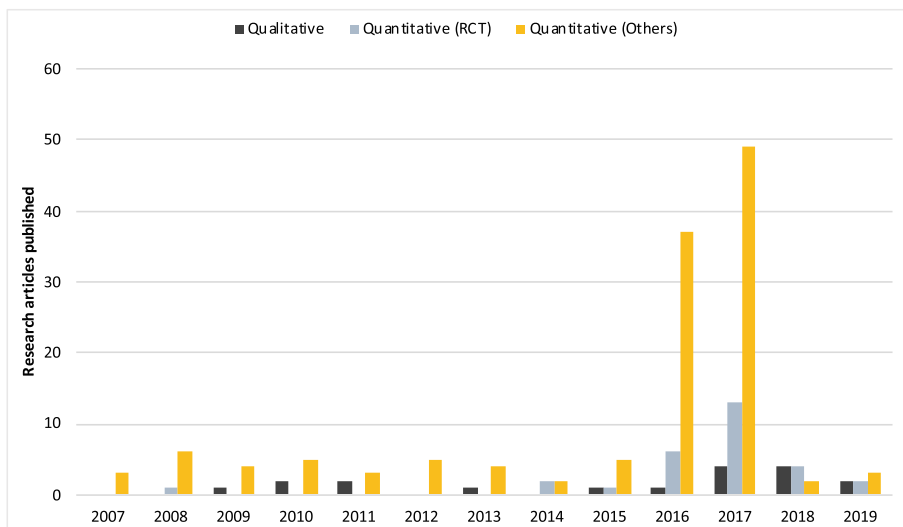
**Fig. 5** Validation of research conducted.
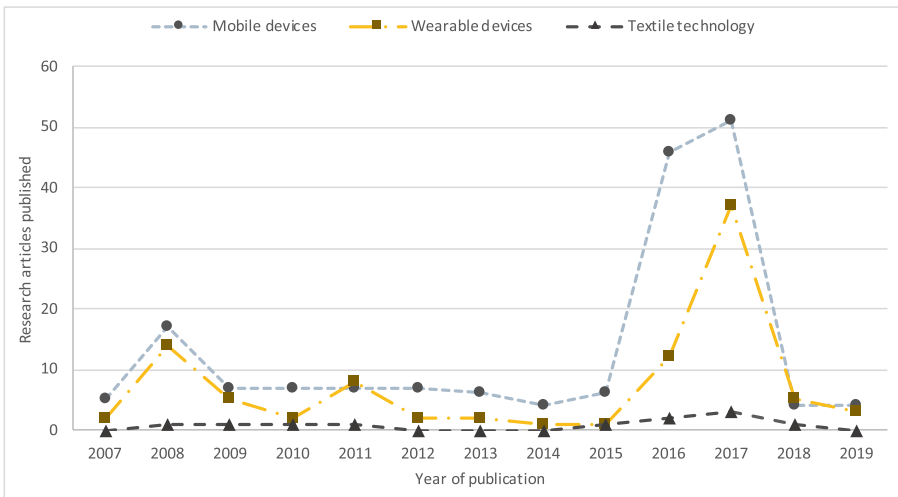
Fig. 6 Comparison of the scientific articles that research continuous health monitoring by using mobile devices or MWT technological approaches.

pectoral zone. Similarly, there are about three times more studies that use wearable devices on the hip/waist ($n = 26$) when compared to mobile devices ($n = 7$).

In general, the least common areas for device placement are the head (3.33% [34, 35, 104, 149, 172]), the upper back (3.33% [42, 144, 160, 174, 179]), and the lower back (1.42% [119, 162]) as documented by the reviewed publications (Fig. 8b).

3.5 Sensing Technology

Due to improvements in sensor technology, it is currently possible to non-intrusively capture motor and metabolic health information via users' physical performance and contact with the skin. For example, wrist smartwatches and forearm bands gather information such as skin temperature, pulse waves, pH, blood flow, and electrodermal activity, whereas smartphones can collect data on long-term performance monitoring [5]. Figure 9 presents a taxonomy of the sensor technologies adopted by the studies retrieved in this scoping review. To offer a better overview of sensor adoption, we
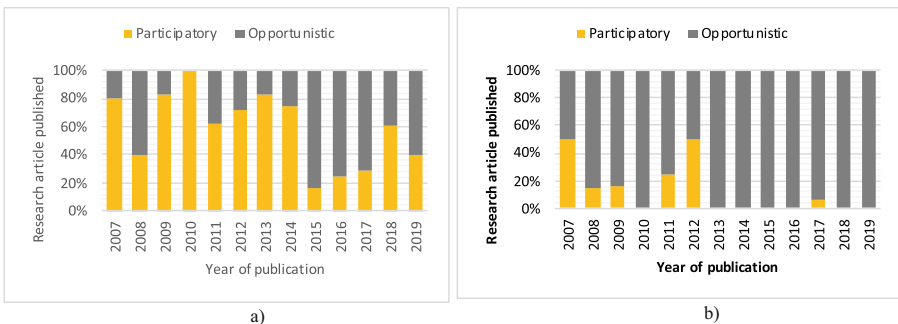

Fig. 7 The sensing approaches used by mobile devices (left) and wearable technology (right). a) Data capture approach of mobile devices, b) Data capture approach of wearable devices.

Table 3 List of articles presenting details from Fig. 7 to illustrate the sensing approach from mobile devices and wearable technology

Year	Mobile devices		Wearable devices	
	Opportunistic	Participatory	Opportunistic	Participatory
2007	[68]	[69–72]	[54]	[72]
2008	[55–63]	[23, 73–77]	[55, 57, 58, 60–63, 73, 78–81]	[76, 82]
2009	[65]	[83–87]	[65, 84, 86–88]	[89]
2010	[64]	[64, 90–92]	[92]	None
2011	[66, 67, 93]	[94–98]	[95, 96, 99]	[98]
2012	[100, 101]	[102–106]	[107]	[104]
2013	[108]	[109–112]	[111, 113]	None
2014	[114]	[24, 25, 115]	[25]	None
2015	[116–120]	[26]	[117]	None
2016	[27–29, 32, 121–148]	[27, 30, 31, 124, 134, 147, 149–155]	[123, 148, 149, 151, 156–161]	None
2017	[37, 43, 68, 162–187]	[39, 42, 174, 183, 188–197]	[34–38, 40, 41, 167, 170, 172, 174, 175, 178, 180, 188–190, 192, 198–216]	[39, 44, 217, 218]
2018	None	[47, 49, 50]	None	None
2019	None	[52, 219]	None	None

excluded experimental cases by focusing on studies in which at least three articles utilise the technology.

In this context, Fig. 9 shows how electrodes and inertial sensing (e.g. accelerometer, gyroscope) are popular technologies used to extract parameters of interest related to medical conditions such as heart rate monitoring, respiration, sleep tracking, and general motor activities.
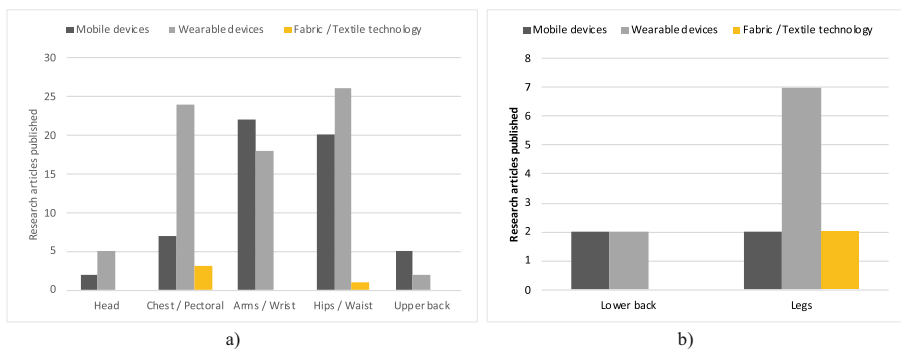
Fig. 8 Comparison of the part of the body where technology is worn/carried. The chart on the left shows the common upper body positions for wearing/carrying devices. The chart on the right shows the common lower body positions for wearing/carrying devices. Note that 88 articles reported having integrated mobile devices as part of a monitoring solution whereby their position was not relevant and not included in the graph. **a**) Upper body position, **b**) Lower body position.
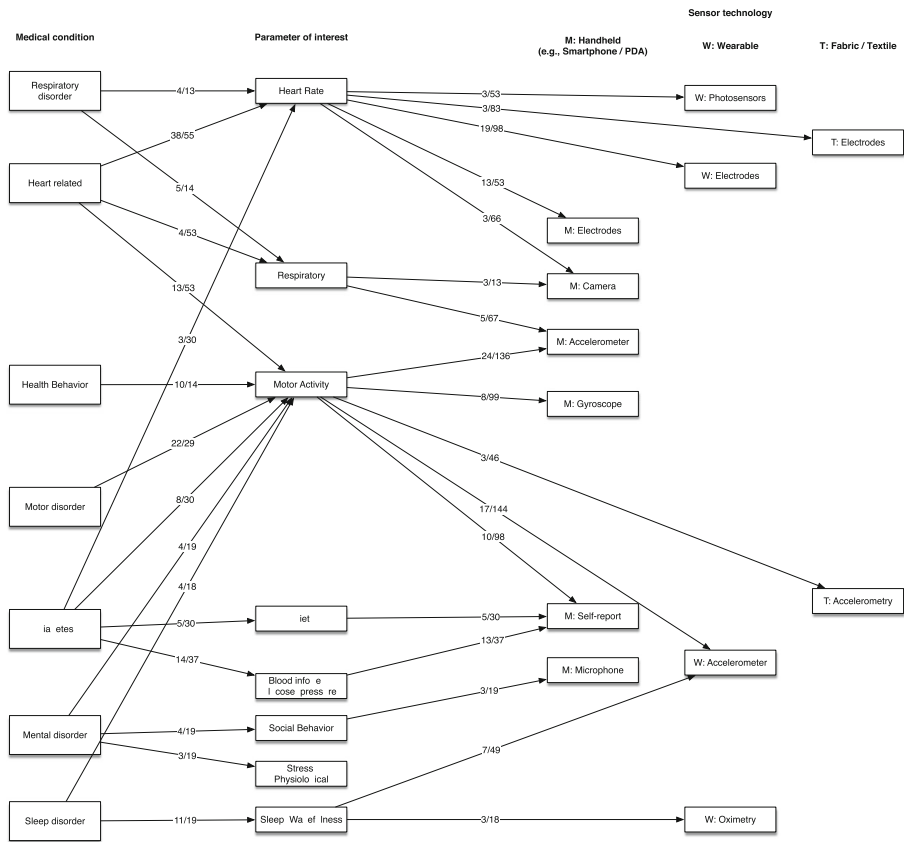
Fig. 9 Taxonomy of sensor technology adopted in research studies to provide detection and monitoring of diseases-related characteristics/parameter of interest. For example, according to this review, a heart rate can be monitored from different perspectives such as photosensors (wearables), electrodes (mobile/wearable/textile), and cameras sensing (mobile).

Although there is a tendency towards mobile and wearable technology, textile solutions are increasing with the increasing use of electrodes and accelerometer sensing. Textile-related projects include the development of adhesive patches that can be worn by users more comfortably; they are usually the actuator of a system in which a smartphone plays the role of a hub to collate and display data [116, 122, 123]. Connectivity is possible using wireless technology, thus increasing users' comfort. Tight-fitting clothes and accessories like gloves and forearm bands enable extended monitoring and a non-intrusive experience.

3.6 Application to Healthcare

The technological application includes behavioural pattern discovery for disease prevention, prediction, and treatment support based on monitoring services. Figure 10 illustrates how heart disorders, followed by wellbeing, are the areas in which most studies have focused (30% and 15%, respectively). The below results omit those cases representing less than 1% of articles; these include projects related to eating disorder

[28, 220], cystic fibrosis [221], dehydration [115, 175], dyskinesia, drug-induced [54], health behaviour [108, 121, 133, 149, 156, 192], musculoskeletal diseases [182], neoplasms [26], obesity [107, 111, 186, 222], peripheral arterial disease [40], ulcer [116], and vision disorder [141].

Heart Disorders This category represents 26.72% of articles that focus on cardiovascular health. According to the 2017 statistics from the World Health Organization (WHO), heart attacks and strokes cause up to 31% of deaths globally (i.e. 17.7 million people every year). Global heart initiatives are being economically supported in order to prevent and manage heart rate conditions as part of primary healthcare [223]. Electrocardiogram data is adopted in current healthcare applications due to its advancements in the physiological monitoring of everyday activities. Studies have demonstrated the feasibility of building passive modules using near-field communication (NFC) devices carried on mobile phones [130]. Others have introduced garments (i.e. brassiere-based) with reliable measurements of up to 89.53% of signals detected and overall user acceptability [123]. From conductive fabric and electrode bands to fabric woven from silver-coated yarn, textile developments are incorporating custom-designed and flexible electrodes to improve practical adoptions in daily situations [224]. The overall aim of the related works is to detect cardiac malfunctions so that family and clinicians are notified and may be able to take some actions that would benefit the patient. They focus on non-intrusive and non-clinical environmental conditions, and a long-term analysis is envisaged in order to produce records for a better understanding of irregular signal patterns.

General Healthcare This section includes studies about technologies to improve wellness [84], mobility monitoring [150], eating behaviour [158], and sedentary behaviour [167], among others. For example, J. Choi et al. [188] propose a service for monitoring personal health states by using smart device-based data extraction and health life ontology modelling using health lifelog analysis. Y. Zhang et al. [148] propose the creation of a remote mobile health monitor system and web service capable of
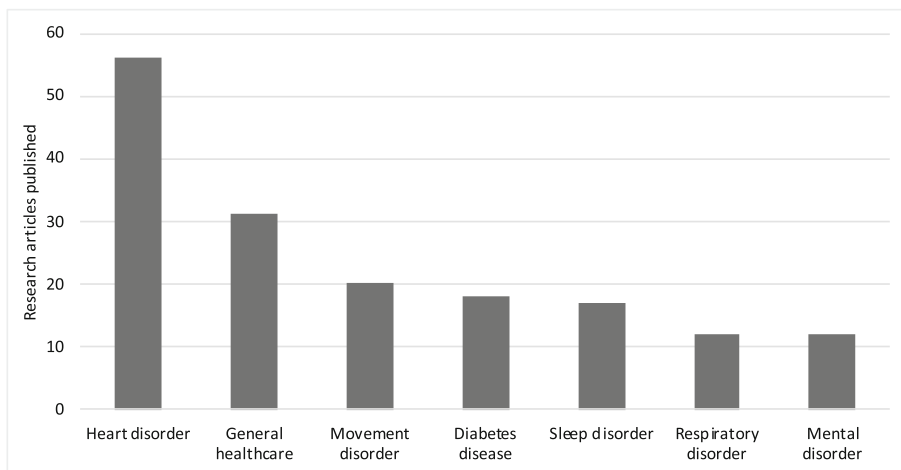
Fig. 10 The number of studies per health condition/disorder.

providing a comprehensive health solution. It can provide doctors and family members with a secure mechanism for remote diagnosis and supports real-time alerts during urgent situations. Their research comprises 14.28% of the articles in this review. Overall, previous works' results show the reliability of monitoring wellness and physiologic parameters associated with patients' health.

Movement Disorder This category includes a wide variety of articles based on motor characteristics such as rigidity, tremor, bradykinesia, hypokinesia, posture, motion control, and similar. It consists of 9.21% of the articles. Medical application varies from gait analysis [119], measuring anticipatory posture towards personalised healthcare [97], epilepsy prediction [172], fall detection systems and algorithms [65], and general activity recognition [174]. For instance, N. Kostikis et al. [131] propose a held or mounted smartphone-based application to assess limb tremor in patients with Parkinson's disease. The examples mentioned above use accelerometers, gyroscopes, and magnetometers, all of which can be micro-electro-mechanical and, when combined, can detect intricate movement patterns. Overall, discussion of device implementation focuses on the devices being low cost, energy efficient, platform-independent, non-intrusive, and requiring no specialised expertise (due to its opportunistic approach). These discussions envision easy clinical examination that happens while patients conduct their daily activities.

Diabetes Disease This category represents 8.29% of the articles. It involves articles that elaborate on glucose monitoring. In general, patients can benefit from sporadic or continuous blood monitoring in order to receive a proper insulin dose. Technological progress is driven towards a self-management approach by integrating wireless features into insulin pumps and analysing the gathered data to build predictive models. Feasible studies suggest that smartwatches and mobile phones could be used as stand-alone devices to continuously monitor sugar levels, insulin injections, physical activity, and dietary information [151]. A theoretical study addresses prototyping systems to self-administer insulin based on statistical models to improve the patient experience [132]. A study on glucose monitoring adherence using smartwatches was investigated in a young population, and it was demonstrated that participatory monitoring behaviour in adolescents is likely to be affected by social context due to the interruption of daily activities and the users' desire to blend in with their peers [109]. In this regard, technological progress is being made by evaluating the user acceptance of wearable devices to monitor vital signs and by building more transparent technology (i.e. non-intrusive and low cognitive demanded) in terms of product design towards friendly use adoption.

Sleep Disorder This category focuses on research addressing quality of sleep, representing up to 7.83% of articles from this scoping review. Disorders such as obstructive sleep apnoea (OSA) are regarded as significant risk factors for diseases that can lead to serious health problems [85]. Snoring is a sign of increased airway resistance and is reported to be a common symptom for OSA. Koo SK et al. [173] recorded snoring sounds according to the obstruction level using a smartphone and focused on the analysis of formant frequencies. They found that spectrographic analysis indicates that retropalatal level obstruction tended to produce sharp and regular peaks.

In contrast, retro-lingual level obstruction tended to show peaks with a gradual onset and decay, giving medical practitioners the ability to analyse snoring in a non-intrusive manner. Garde A. et al. [145] presents a validation in which a phone oximeter is compared against polysomnography, the gold standard for OSA diagnosis, which is resource-intensive and requires a specialised laboratory. The increasing demands for home-based sleep monitoring have prompted the development of devices that monitor sleep using fewer sensors. Other approaches use acceleration and angular velocity obtained from built-in smartphone sensors and then applied a wavelet denoising technique to minimise the nonstationary noise [117].

Respiratory Disorders This section represents 5.52% of articles that elaborate on aspects of human ventilation, particularly pulmonary-related. Patients suffering from dyspnoea, chronic obstructive pulmonary disease, or asthma can be monitored for early detection of symptoms and the administration of treatments after hospital interventions. In this regard, the convergent validity of accelerometer and self-reported activity data have been presented as evidence of the feasibility of assessing the respiratory condition in different populations. For example, in children diagnosed with asthma [87], patients with chronic obstructive pulmonary disease [29, 179], and healthy subjects [142] (in which findings report from moderate to high), there is an agreement between estimates of exertion made using sensor data and those reported by participants. Other examples include Il Hyung et al., who present a study conducted in early 2007 in which they monitor oxygen saturation by using the Sp02 module sensor. They combine data with electrocardiography (ECG) and a global positioning system (GPS) to illustrate the geographic walking routes in which users experienced the highest demand of oxygen [60]. Under a more non-intrusive mechanism, N. Hernández and J. Favela [225] propose a model and mobile application to identify elderly physical fatigue based on a correlation between heart rate, oxygen consumed, and physical fatigue perceived by participants.

Mental Disorder This section represents 5.52% of the articles. It includes application of psychosomatic research for diagnoses such as schizophrenia [102], bipolar disorder [27], ruminative self-focus [25], emotional monitoring [160], and social rhythms [185], among others. Although some projects rely on self-report mechanisms, [194], automatic solutions are more common in recent years. Efforts included the Electronically Activated Recorder (EAR), which consists of periodical audio recordings that non-intrusively record snippets of ambient sounds from users' environments [101]. An audio sensor has also been used for detecting bipolar disorder, yielding acoustic logs of people's day-to-day activities as they naturally unfold. For instance, A. Guidi et al. [155] developed an Android application for analysing speech while using a smartphone device. Their results demonstrated that speech frequency could be reliably estimated, thus describing prosodic features across the audio sample.

Overall, those articles representing less than 1% of the contribution involve the design and development of studies and projects associated with the identification of health-related patient characteristics that could further be addressed by particular disease monitoring. Characteristics include (but are not limited to) weight loss [186], temperature [199], oncology practices [26], dynamic compression [182], and body mass index [192]. Moreover, platform designs and software frameworks are also taken

into account [121]. For instance, Becher K. et al. [67] describe a wireless sensor gateway that allows recording of bio-signals such as electrocardiogram, pulse wave, and body weight. It has the distinctive feature of using two different radio transceivers, exploiting the advantages of technology for constant monitoring. More non-intrusive approaches are being developed; Chung P. et al. [116] propose the use of a Bluetooth-enabled fabric-based pressure sensor array to assess and continuously monitor decubitus ulcer risk. Although this particular project is still only implemented as a prototype, their invention could positively affect mobile healthcare applications.

4 Discussion

Traditional medicine diagnoses, clinical interventions, and rehabilitation treatments require patients to be monitored over time, which tends to be cumbersome and expensive. MWT technology opens the possibility of using sensor technology to build solutions for the prevention of disease through continuous monitoring. This scoping review examines how MWT technology has been improving healthcare by offering alternate solutions to challenging issues based on non-intrusive patient monitoring.

Overall findings in this review demonstrate that using mobile and wearable devices for automatic monitoring of mental behaviour is a feasible approach and a key marker of wellbeing for monitoring individuals with health conditions. Moreover, due to approximately 90% of our bodies typically being covered by clothing, the use of smart garments is promising [131]. By using mobile technology, the analysis of sensor data can be a useful screening test for the prediction of occlusion on a daily basis.

Publication Trends Some of the figures reflect a stark increase of publications in some years, notably in 2016 and 2017. There are some plausible explanations for these spikes. For instance, the Apple Watch was launched in 2015, which could have attracted attention to commercial gadgets. Also, consumer electronics and research technology could be more mature by the time of publication. PubMed does not typically index conferences, where much of the work-in-progress research could have been published.

The Technology Used For this study, it can be argued that wearable devices (e.g. physical activity trackers, smartwatches) have a low level of intrusiveness since they are expected to be worn rather than carried by the user (as is the case with most studies involving mobile devices used for monitoring purposes). Setting restrictions have been discussed in different articles [226], indicating that results and interpretation outcomes are likely to vary depending on the device's physical orientation and location.

Participatory vs Opportunistic Sensing Due to the rapid adoption and availability of off-the-shelf technology, smartphones started to be conceived as tools to capture information (as reported by the 80% of the article considered in this study). The year of 2007 represents the beginning of building databases based on associating activity performance with sensor data by using the labelling approach, where users were mostly asked to enable data recording while carrying sensing devices. Similarly, other studies

required users to manually capture self-assessment measurements [69–72]. Still, it can be seen that the in the case of smartphone-based studies, a great percentage use the participatory sensing approach. This can be explained by the nature of the device, having sensing capabilities as well as ways to provide feedback (e.g. keyboard and display). Along these lines, this can also explain why wearable-based studies focus on using the opportunistic sensing approach, as many of these gadgets are mainly worn to collect data from specific parts of the body (e.g. legs) or because it is conventional (e.g. wristwatch).

Research Evaluation Evaluation is maturing in different ways. For instance, 68.01% ($n = 151$) of articles found in this scoping review consist of prototyping ($n = 103$) and proof of concept for research purposes ($n = 48$), whereas 18.46% ($n = 41$) corresponds to commercial systems, and 5.40% ($n = 12$) to devices' clinical approval. Similarly, considering that the strength of evidence is stronger in quantitative research, particularly concerning RCT, results from this scoping review show that since 2014 the percentage of studies conducting RTC ($n = 28$) has doubled compared to qualitative studies ($n = 12$). The doubling can be explained by the relative length of time that it can take to plan, execute, and publish an RTC study, as compared to other types of studies. Also, the increase of other types of studies (such as quantitative) may be the result of technology advancement, as mentioned in the previous paragraphs.

Sensor Technology The concept of computing is rapidly expanding from using desktop computers to portable computation devices that have sensors and access to a network. Traditional sensor capabilities consist of detecting sounds, images, body motion, or ambient light level. However, advances in technology are quickly evolving. Embedded sensors can now transmit biochemical (glucose, chemistries) and physiological (skin temperature, electroencephalogram, blood pressure, blood oxygen saturation, respiration rate heart rate, electrocardiogram, cardiac output, and weight) information from the user as it is carried or worn, with information sent to remote processing units. Sensors are becoming so small and flexible that they are unobtrusive; either woven into clothing or laminated onto ultrathin skin interfaces and placed on the human body. As more sensors become available, there will be more studies on possible uses. Perhaps much more important, as more consumer electronics or digital health devices are cleared by the FDA, we can expect more studies that can include them in RCT studies.

4.1 Reflections for Future Research

As we read through the literature included in this study, we observed that their qualitative findings reported comparable practices across the computing technology, medical informatics, and engineering disciplines when building solutions for monitoring health. Since the majority of the contributions consisted of prototypes and early implementations, we believe that reporting such insights would be particularly valuable to our community by accelerating the development of emerging prototypes into operational pieces of technology. Our observations can be summarised into four guidelines:

Unobtrusive Approach to Data Gathering Given the wide variety and accessibility to MWT sensing devices, one's technology selection should be aligned with the user's acceptability. As reflected by the articles reviewed, one approach is the adoption of unobtrusive monitoring, where the sensing devices are worn/carried by the user without interrupting their normal activities. By using this approach, medical professionals could monitor patients in real time and during more extended periods than those that are possible during a hospital stay or a visit to a physician's office. These systems could then provide real-time processing and feedback to medical staff, patients, athletes, and even issue alerts in the event of an emergency.

Creative Use of Sensing Technology Each piece of sensing technology brings particular characteristics to the sensed data, so one should have a creative mindset when developing products that provide the clinical information required (parameter of interest) without compromising the comfort of wearing/carrying the sensing devices. When the revised articles were organised over application topics across the sensing technology, they revealed how creativity is an essential attribute when building monitoring technology. In Fig. 9, we can see how sensing technology from different feature spaces is utilised to build solutions yielding a similar parameter of interest regardless of wireless communication constraints, processing capabilities, power supplies, storage capacity, or physical dimensions.

Evidence Supported by Clinical Practices One should focus on conducting robust evaluations to produce high-level, credible evidence [227]. A randomised controlled trial [228] is a standard clinical practice recently adopted by the engineering community. RCTs can reduce certain sources of biases, thereby increasing the influence results have upon the stakeholder (e.g. regulators, practitioner, patients, federal organisations) [229].

User-Centred Design The explicit understanding of the end user is essential when developing a useful and usable piece of technology [230]. As observed across the reviewed articles of this study, conducting user-centred examinations at the design stage contributes insights that will facilitate acceptability, engagement, and usability. This approach can accelerate the deployment and adoption of novel technology while developing effective pieces of computational technology to continuously monitor health.

5 Conclusion

Health-related needs are changing, and people want to be more involved in the management of their health, preferring painless methods of diagnosis and treatments. In this regard, there is a trend towards effortless and painless methods of diagnosis and treatment moving from traditional institution-centred care towards a patient, citizen-centred one. The ubiquity of information technology and the increase of computational capabilities open opportunities for continuous health monitoring systems by wearing or carrying day-to-day devices such as smartphones, smartwatches, smart clothing, and

fitness trackers. In this study, we present the current literature on how mobile, wearable, and textile sensing technology has influenced the medical field by bringing technological solutions to problems in which continuous monitoring is essential.

This scoping review follows the PRISMA review protocol. We present an overview of 222 articles retrieved from PubMed. Of these, 101 articles (45.5%) have been published in medical journals, 60 articles (27%) were published in multidisciplinary journals and 41 articles (18.5%) in proceedings, while 14 articles (6%) were published in engineering journals and 6 articles (3%) were published in proceedings. Although most of the studies reviewed used quantitative methodologies, results show an escalation in the number of articles adopting standardised clinical methodologies such as RCTs (currently rating to 13.5%). With regard to the technology and data collection approach, a majority of the participatory sensing approach studies rely on mobile devices such as smartphones (77%), with a contrasting interest in the adoption of opportunistic data collection approach when using wearable sensing technology (91%).

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