Biomechanics Beyond the Lab: Remote Technology for Osteoarthritis Patient Data - A Scoping Review

Rebecca I. Hamilton (hamiltonr@cardiff.ac.uk)
Cardiff University https://orcid.org/0000-0003-1241-6671

Jenny Williams
Cardiff University

OATech Network+ Consortium
Osteoarthritis Technology NetworkPlus

Cathy Holt
Cardiff University https://orcid.org/0000-0002-0428-8078

Systematic Review

Keywords: biomechanics, inertial measurement units, remote technology, osteoarthritis, gait analysis

Posted Date: June 29th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1792649/v1

Abstract

The objective of the project was to produce a review of available and validated technology suitable for gathering biomechanical and functional research data in patients with osteoarthritis (OA), outside of a traditional fixed laboratory setting. A scoping review was conducted using defined search terms across three databases (SCOPUS, OVID MEDLINE, and PEDRO) and additional sources of information from grey literature were added. One author carried out an initial title and abstract review, and two authors independently completed full text screenings. Out of the total 5,164 articles screened, 75 were included based on inclusion criteria covering a range of technologies in articles published from 2015. These were subsequently categorised by technology type (wearables-IMUs, wearables-other, insoles/platforms and cameras) and metric (kinematic and spatiotemporal measures (SPTs), kinetic and SPTs, joint angles/ROM only and EMG), and as suitable for portable, part remote or remote use. Those technologies that are commercially available were also identified.

Results concluded that from the growing number of available and emerging technologies, there is a well-established range in use. These are primarily inertial measurement units, as well as other wearables and camera-based technologies, particularly for collection of gait SPTs. Results demonstrate that biomechanical and functional remote data collection is both feasible and has growing potential for OA researchers.

1.0 Introduction

1.1 Research Objective

Osteoarthritis (OA) is a highly prevalent global disease. With no cure, and no proven interventions able to stop its' progression (OARSI 2016), it is a major cause of disability worldwide with increasing prevalence. The consequences of OA impact significantly on individuals and wider society (Versus Arthritis 2021), highlighting the urgent need for increased investment into large scale scientific and clinical research (Vitaloni et al. 2020).

For research purposes, several common minimally invasive biomechanical (kinetic, kinematic, and spatiotemporal (SPT)), measures are used to assess OA disease progression and outcomes following interventions (e.g., total knee arthroplasty). These are commonly extracted from human gait and include basic movement parameters with related ground reaction forces (GRFs), joint angles/moments, and range of motion (ROM) (OARSI 2016). The recommended performance measures to evaluate hip and knee OA (30 second chair stand, 40m fast-paced walk, stair climb, Timed Up and Go, 6-minute walk) can be challenging for clinicians and researchers in standard fixed-assessment environments and lack real-life representation (Dobson et al. 2012).

The driver for larger scale biomechanics research outputs within OA conditions is supported by the increasing availability of newly developing technology (Mangal and Tiwari 2021). The OATech Network+ (Sawle et al. 2017) is a collaborative UK based research network developing technology solutions for OA and identified novel and emerging technology advances should play a key role in directing OA research diagnosis, treatment and monitoring (Mennan et al. 2020).

Though the path towards remote data collection was forged before the Covid-19 pandemic, it has provided strong impetus for researchers to seek methods that enable OA research to be performed at a distance, increasing accessibility whilst minimising risks. Additionally, there is strong evidence that the Covid-19

pandemic has increased acceptance of technology in healthcare from the perspective of both the patient and clinician (Horton 2021). Though a large body of work for existing biomechanical and wearable technology exists, there remains a lack of evidence that reviews and identifies their availability (commercial or experimental) that have been validated across the gold standard technology familiar to OA researchers. To date, no papers have been identified that focus on available biomechanics technologies developed specifically for use outside the lab or for remote use by OA researchers. Therefore, in this current scoping review, the objective is to summarise available technology that has been validated against a researcher recognised gold standard technology to confirm its ability to deliver data that is comparable with established systems and technology found in traditional research laboratory settings. By reviewing recent technological developments, an indication of the future direction of remote OA research can also be established.

1.2 Technology Background for Remote Biomechanics

The increased desire amongst biomechanics researchers to identify and adopt technology that can be used remotely is driven by a combination of factors (Drazan 2021). Studies that require quantified and objective human gait characteristics have highlighted the benefits associated with gathering real-world measurements; defined as being outside the laboratory, or 'non-scripted' walking, due to the inability of clinical laboratories to reliably reflect daily-living measures (Kluge et al. 2021). Distinct differences in gait measures between these environments have been identified by several studies (Brodie et al. 2016; Urbanek et al. 2018; Hillel et al. 2019; Takayanagi et al. 2019), suggesting that data gathered outside a laboratory setting can more accurately reflect real life walking speed and ability. In parallel to these studies, the technological landscape has transformed in recent years, profoundly influencing healthcare, suggesting new possibilities for biomedical research (Elenko et al. 2015).

Technologies that are currently in widespread use for instrumented kinetic, kinematic and SPT measures can be classified broadly into two different approaches (Muro-de-la-Herran et al. 2014), based on data gathered in a required and controlled fixed-environment and data gathered via wearable sensors (WS) that can be used freely. Fixed research facilities can house recording equipment and sensors to capture gait. They often employ established motion capture (MoCap) technology involving 3-Dimensional (3D) optical retroreflective marker-based systems with multiple video cameras (e.g. Qualisys, Vicon, Optitrack) and strain gauge instrumented force plates (e.g. Bertec, Kistler) measuring GRFs and/or pressure sensor force resistive values (e.g. TekScan, GaitRite). These can compute accurate 3D joint biomechanics measures using inverse dynamic mathematical models but are dependent on human accuracy of marker placement and laboratory calibration to reduce technical errors. These are commonly considered the gold standard and widely regarded as the most accurate approach to collect human clinical biomechanical measures such as clinical gait analysis (Kressig and Beauchet 2006; Wren et al. 2020; CMAS 2021). Although described as the 'widely accepted convention', it is acknowledged that inertial measurement units (IMUs) and mobile technologies present researchers with potential access to objective measures of gait in unconstrained environments (Allseits et al. 2018). WS incorporating IMUs have been found with similar sensitivity to detect gait kinematic changes (Lee et al. 2019) and good levels of accuracy and consistency for gait SPTs when compared to optical motion capture (Rudisch et al. 2021). They are growing in popularity as a valid alternative to the more expensive and fixed systems with more environment flexibility and range of measures (Teufl et al. 2018; Werner et al. 2020).

Body-worn WS systems often include use of an accelerometer and recently reviewed as the most common technology for monitoring knee OA patients (Cudejko 2021). IMU systems in regular use (e.g. XSens, Wearnotch), collate information gathered from 3-axes accelerometers, gyroscopes and magnetometers within each sensor. These provide raw data that are computed into kinematic outputs (joint angles, segment velocity, segment acceleration etc.) based on the subject calibrated model and subsequently into meaningful gait SPT parameters (Werner et al. 2020). Each type of WS system has individual capabilities and considered to have lower reliability compared to optical motion tracking, though accepted measurement resolutions have been examined clinically (Teufl et al. 2018). The use of more portable equipment with clinically accepted accuracy levels (Kluge et al. 2018), allows better integration of gait analysis into clinical routines. With IMU research growing at an exceptional rate, the growth of available parameters to analyse OA patients has therefore expanded based on individual IMU features computed (Petraglia et al. 2019). The evaluation of different ubiquitous commercially available IMUs suggests that, selection should be dependent on the requirements of the research question, due to the potential array of parameters and collection methods, thus resulting in limitations within standardised IMU protocol methods (Zhou et al. 2020).

There is increasingly available supplies of lightweight, portable and accurate tools for remote measurements and monitoring due to the evolution of cheaper integrated circuits, the development of technology integration and emerging sensing techniques (Nascimento et al. 2020). For example, stick-on skin gauges (Sun et al. 2020) and self-functioning textiles for gloves, garments and socks (Zhu et al. 2019) recording OA relevant measures. Force resistive technology is used often within laboratory environments for OA movement biomechanical analysis, however, as a remote technology it has a strong consumer application for physical activity and sports monitoring (Benson et al. 2018; Walmsley et al. 2018).

The evolution of more powerful algorithms to convert data harnessed by sensors into clinically meaningful outcomes has also accelerated the use of mobile technologies in clinical research (Bakker et al. 2019). Their level of acceptance within patient and health related contexts has increased with their usage (Zhu et al. 2019). As well as the increased opportunities for researchers, advances including wireless connectivity, real-time information and advanced visualization, have led to this technology penetrating the consumer market (Peters et al. 2021) with individualised measurement now possible (Morgan et al. 2020). Importantly, current evidence suggests technology is producing a positive impact on OA treatment (Schafer et al. 2018) allowing patients to manage their own condition, and record their own outcome measures, while motivating and informing users in real time.

The development of Red Green Blue-Depth (RGB-D) sensing camera technology, in particular the launch of the Microsoft (Microsoft Corporation, USA) X-Box Kinect camera in 2010, and other commercially available products including Asus Xtion Pro (ASUSTeK Computer Inc. USA), Intel RealSense (Intel Corporation, USA) and Orbbec (Orbbec 3D Technology International Inc USA), is perhaps one of the most significant developments in biomechanics and clinical research, offering a cost-effective marker-less solution to overcome the limitations of marker-based motion capture. A review of the use of RGB-D sensors for musculoskeletal health monitoring has revealed a lack of validity assessment and although the algorithms for 3D joint parameters are found to be acceptable, there are still limitations (Mangal and Tiwari 2021). Though camera based skeletal tracking has accuracy limitations (Abedtash and Holden 2017), advances in marker-less motion capture will likely change the future of data collection for biomechanics (Halilaj et al. 2021). These systems offer potential to deliver an

alternative approach with practical benefits for both fixed and WS due to the ability to capture data in any environment where cameras can be set up (Latorre et al. 2018; Milosevic et al. 2020).

2.0 Methods

A scoping review format was selected to synthesise research and technology developments in this broad area. This approach would review and summarise available evidence as a preliminary and structured assessment whilst allowing for an overview on the extensive topic. The approach was based on the Preferred Reporting Items for Systematic Reviews Scoping Review Protocol (PRISMA-Scr) (Peters et al. 2020) which was revised by the research team and members of the OATech + Network Plus Operations Group.

The review was conducted following a five-step process: (1) definition of the research question (2) creation of a research strategy to identify relevant studies for inclusion (3) study selection (4) collation and charting of results and (5) analysis and reporting of results.

2.1 Definition of the research question

To address the research objective, the primary research question (RQ) of this review asked:

1. What technologies are available for gathering kinetic or kinematic data for OA research purposes outside of a laboratory setting?

The review also asked additional secondary research questions:

2. Is the identified technology validated against an existing gold standard technology?

3. Is this technology suitable for use in a remote context and if so, is it portable, partly remote, or fully remote (see Table 2)?

4. Which of the technologies can be identified as commercially available and therefore available for the researcher to acquire?

Therefore, papers were only included if the technology itself was the subject of the research and there was evidence of validation through human testing. This review aims to identify available technologies being used within different settings and addressing the above parameters and provide a narrative overview; however, does not quality assess the technology.

2.2 Search Strategy

The search strategy was designed by the core research team with the support of a subject librarian and a specialist researcher. A broad literature search was undertaken in three main databases: SCOPUS, OVID MEDLINE, and PEDRO using an individual search strategy for each. Grey literature searches and reference list scanning was undertaken manually. All search criteria and dates searches were conducted are listed in Supplementary Material.

All articles were uploaded to EndNote software (V20.1.0.15341) where duplicate titles were removed. Title and abstract screening was completed by author (Williams J) and full text screening carried out by two authors

independently (Williams J, Hamilton R I) with any conflicting views discussed and agreed.

2.3 Study selection

Of the 5165 papers originally identified, 376 papers were eligible for full text review after duplications and first screen abstracts were removed (Fig. 1).

The papers were selected if they met the following inclusion criteria:

a) the focus of the study included an identified technology capable of measuring relevant biomechanical or functional parameters recognised as characteristic for OA, e.g., spatiotemporal, gait, force, or pressure. Metrics that were not considered relevant for OA research, e.g., vertical drop jump, were excluded.

b) the study described the results of validation of the technology against gold standard laboratory grade equipment (defined in Table 1).

c) the study was an original article in a peer reviewed journal and published between the period of 2015–2021. This date range was selected due to the rapid pace of technology development.

d) the study was written in the English language. As the OATech + Network Plus is an English-speaking network led in the UK, only papers published in English were included.

e) the study gathered data on live human participants. No conditions were excluded, the determining factor was the parameter determined in a).

f) the study demonstrated the technology capability to collect data outside of a fixed laboratory setting (despite most validation studies would be performed in a traditional setting). The study description of the technology capability of adoption remotely/portably was considered sufficient. A traditional fixed laboratory setting was considered one where there is fixed equipment, e.g., multi camera systems/embedded floor force plates.

Table 1
Definition of gold standard for the purposes of the current study included commercially available products in widespread use.

Motion capture, video, and optical tracking equipment	**Vicon (Vicon Motion Systems Ltd.), Qualisys (Qualisys AB, Sweden), Optitrack (Naturalpoint Inc. USA), Optotrack Certus (Northern Digital, Canada), NDI Polaris Vega (Northern Digital, Canada), SmartDX (BTS Bioengineering Corp, USA), Cortex (Motion Analysis Corp, USA)**
Instrumented force plates, treadmills and walkways	Zeno (Protokinetics LLC, USA), Gaitrite (CIR Systems Inc, USA), NeuroCom SMART Balance Master (NeuroCom International Inc. USA), Bertec (Bertec Corp, USA), AMTI (Advanced Mechanic Technology Inc. USA), Zebris (zebris Medical GmbH, Germany)
Previously validated human movement IMU systems including insoles	Xsens (Xsens Technologies BV, Netherlands), Medilogic (T&T Medilogic Medizintechnik GmbH, Germany), InertiaCube (Intersense Inc, USA), Wearnotch (Notch Interfaces Inc. USA), APDM Opal (APDM Wearable Technologies Inc. USA), Parotec (Paromed gmbh & Co. Germany)
Standard clinical tools	Manual goniometer, Electro-goniometer, Radiography
EMG systems	Delsys EMG (Delsys Inc. USA)

Papers were excluded if their study focus was based on algorithm models under development without analysis of the hardware technology and its data collecting abilities. Papers were excluded if the technology under review could already be considered gold standard and the paper was demonstrating its existing use or a new application.

2.4 Collation of Results

Data from each article were collated (Table 3) including author, title, technology in use, parameters gathered, availability, e.g., commercially available, or experimental only, and the degree to which the technology was intended for remote use (Table 2).

Table 2
Definition terms for degree of technology remoteness.

Portable	**Requires static research suitable environment which could be a clinic or community setting where data is gathered at a defined location.**	**Requires specialist trained users to operate whilst data is gathered, cannot solely be participant operated**
Part Remote	Able to operate in most environments but has some environmental requirements e.g. range, connectivity, wired etc	Requires specialist trained users to support set up / harvest data but data can be gathered without specialist present.
Fully Remote	Able to operate in any environment or setting e.g. home, clinic, outdoors. Participant is unrestricted and unobserved during data gathering.	Capable of being used and managed by a non-specialist individual (or participant) with minimal support / training during data gathering

The technologies were then identified by type into four main categories agreed by the research team as: 1. IMU based wearable technology, 2. Non-IMU based wearable technology, 3. Camera based technology, and 4. Insole based technology. Technology was also reviewed by parameters recorded, by the degree to which it can be used remotely, and into a separate table of commercially available technology as a subset of the results.

3.0 Results

3.1 Study selection

Figure 1 illustrates the literature search and exclusion criteria with further exclusion details in Supplementary Material (Table 2). Following the search strategy within three databases (Methods 2.2), 376 full articles were assessed for eligibility from which 75 were identified for inclusion within the final screen (Fig. 1).

3.2 Technology themes

The remaining articles were assessed and recorded categorically depending on broad technology type, location of use, metrics being measured and their commercial availability (Table 3).

Based on the range of results, technologies were categorised into four main technology types with some meeting classification criteria more than one category. A large percentage of technologies identified as wearable devices, these were split into those consisting of ‘IMUs’ and ‘other wearables’. The remaining two categories were ‘cameras’ and ‘insoles/platforms’ using force resisting sensor technology. Figures 2–4 demonstrate the division as well as the overlap of the technology type, metrics recorded and location. ‘IMU wearables’ (Fig. 2) are

the most prominent technology type, ‘kinematics with SPTs’ (Fig. 3) is the most prominent metric recorded and ‘part-remote’ (Fig. 4) is the most used application of the technology screened.

The description of metrics used was also divided into four main categories described below (Table 3), dividing the metrics based on kinetic and kinematics as well as further divided into use of joint angle/ROM, SPT and EMG data collection. The application of the technology was divided into three main categories based on the definitions described in Methods section 2.4 (Table 2) and the commercially available status of the technology was based on the information available in the article with further details on these in Table 4.

3.3 Commercially Available Technology

Within the 75 articles, 57 different technologies were identified, the majority of these experimental or made use of a commercially available component, e.g., IMU, smartphone, activity monitor, RGB cameras, virtual reality (VR) headsets, optical tracking devices or video game hardware components. Whilst some of these components are commercially available, only technologies that are commercially available as a complete system (both gathering and displaying results for their described use) appear in Table 4. 12 papers referred to use of the Microsoft Kinect V2 camera, now retired and therefore does not feature in Table 4. 1 paper referred to a previously commercially available product Hasomed RehaGait (HASOMED GmbH, Germany), retired as of December 2021, therefore excluded from Table 4. The current or future availability of each of these technologies has not been verified.

Table 4. Identified commercially available technology with related corresponding information and study reference in which it was evaluated.

	Description	Metric	Location	Study Reference
BioStamp https://www.mc10inc.com/	Skin adherent sensor patch with accelerometer and gyroscope (IMUs)	Tri-axial linear/angular motion, ROM, joint angles, gait SPTs.	Part Remote	(Moon et al. 2017; Ammann et al. 2020)
Echo5d from Atlas5D https://atlas5d.com/our-technology/	Ambient measurement system – non wearable activity monitoring	Gait SPTs - ADLs	Part Remote	(Bethoux et al. 2018)
Encephalog from Mon4t https://mon4t.com/movement/	Smartphone app (integrated tri-axial accelerometers and gyroscopes).	Gait SPTs – specifically in relation to TUG parameters.	Remote	(Tchelet et al. 2019)
GaitSmart https://www.gaitsmart.com/	IMU's with proprietary software	Gait SPTs, ROM, kinematic parameters.	Part Remote	(Zügner et al. 2019; Van Helvoort et al. 2021)
Loadsol https://www.novelusa.com/loadsol	In shoe worn insole device	Plantar peak force.	Part Remote	(Renner and Queen 2021)
McRoberts Dynaport MoveTest https://www.mcroberts.nl/products/movetest/	Single IMU belt worn device	Gait SPTs.	Portable	(Werner et al. 2020)
OpenGo by Moticon https://moticon.com/opengo	OpenGO (wireless shoe insole) with Moticon smartphone application	Kinetic parameters (KAM), gait SPTs.	Portable	(He et al. 2019)
Physilog GaitUP https://research.gaitup.com/physilog/	Two Physilog IMU's and proprietary Gaitup software system	Gait SPTs.	Part Remote	(Lefeber et al. 2019)
SensFloor https://future-shape.com/en/gait-recording/	Capacitive sensor embedded flooring with recording outputs	Gait SPTs.	Part Remote	(Lanzola et al. 2020)

	Description	Metric	Location	Study Reference
Theia3D Markerless https://www.theiamarkerless.ca/ In conjunction with Qualisys (Qualisys AB, Sweden) Miqus cameras	Marker-less motion capture software for processing of camera generated video to produce 3D kinematic data (segments and rotation matrices) that is ready for analysis.	Kinematic SPT's, segments, angles.	Portable	(Kanko et al. 2021)

4.0 Discussion

Considering the review objective to identify technology suitable for biomechanical data gathering outside a laboratory environment (RQ1), the refined list then resulted in technology with sufficient gold standard validation (RQ2), with evaluation on technology level of remoteness (RQ3) and commercial availability (RQ4). With a considerable number of results and experimental technology under development, there is growing interest and feasibility for research in this field from numerous groups.

With almost 75% of the technology identified as participant wearable technology – body fixed, or shoe worn, this gives rise to both individual needs of data collection methods and types, as well as their range of potential in different uses. The remaining quarter focussed on camera technology with growing prevalence of marker-less MoCap (Kanko et al. 2021) being used, though predominantly still within laboratory settings but with a degree of portability. 75% of the technology identified is focussed on lower limb, as expected, with gait and SPT metrics as prevalent outcomes. Gait SPTs were the most common and therefore, expected to be the most valuable; less valuable were the 2 studies using EMG technology.

4.1 Technology Types

4.1.1 Wearables - IMU

The range of methods, protocols, population groups and overarching contexts used within the IMU studies indicate the extent of their potential as well as supporting previous observations stating their considerable commercial availability. Most studies using IMUs were interested in SPT outcome measures, in agreement with previous evaluation of IMUs for OA research (Kobsar et al. 2020), as a highly useful clinical evaluation tool. Mainstream use of IMU technology was found to be prevalent for studies collecting kinematic parameters in clinical, research and rehabilitation settings (Small et al. 2019), with a small number of IMU studies focussed on predicting joint angles and ROM measures (Oubre et al. 2020). These technologies were all developmental, apart from the use of Shimmer IMUs (Oubre et al. 2020). This indicates a field of research that is cumulatively gaining interest, however, requires increased complexities of computational predictive modelling to produce joint

angle data due to the information required from 3-axes data and related biomechanical models when compared to camera-based produced measures.

Most IMUs were demonstrated as belt or strap worn devices, however, emerging in two studies (Ammann et al., 2020; Moon et al., 2017) is a commercially available skin adherent IMU; Biostamp (BiostampRC, M10 Inc. USA), found to be well suited to a variety of uses including potential granular monitoring of gait both inside and outside the clinic (Moon et al. 2017). A variety of experimental systems were found reporting on IMU data collection alongside a mobile application (Aqueveque et al 2020, Li et al., 2020) and visual user-feedback (Bell et al., 2019) with good accuracy and platform outputs for joint angle measurements, demonstrating strong potential for reliable home-based rehabilitation data collection.

Several studies revealed positive patient acceptance and usability for IMU wearables (Papi et al. 2015; Belsi et al. 2016; Bell et al. 2019). However, all IMUs identified in this review were considered suitable for part remote use only, requiring expert support due to specific requirements around their placement or connectivity. Therefore, despite the evidence that they provide solutions to remote data collection protocols, the level of support required for their set up and data acquisition means they are unlikely to be suitable or utilised for long-term at home data collection.

The variability of IMU data collection methods and lack of consensus in terms of standard measures, IMU positioning, or approach offers researchers flexibility for application however it decreases the ability to compare and utilise shared data and results (Aqueveque et al. 2020). Aqueveque provided recommendations for IMU data collection methods for SPT parameters towards the standardisation of IMU data collection methods, however, further pragmatic guidelines using validated methods are required to aid future remote gait assessment where environmental unknowns will complicate data interpretation (Celik et al. 2021).

4.1.2 Wearables - Other

This technology group is dominated by small consumer grade devices, e.g., activity monitors, VR headsets or consumer smartphones containing accelerometers, gyroscopes and cameras. The value of these technologies is their level of remoteness, since many of them are comprised of smartphone technology, as consumer grade devices with simple user interfaces. Six out of the seven ‘fully remote’ technologies were in this category and used smartphone application software. Therefore, this is likely to be a successful route for true remoteness of data collection methods. Though growing in popularity, the current ageing population is prevalent within the OA population requiring rehabilitation, thus usability and reliability may still be limited (Belsi et al., 2016). This is supported by mixed results for SPT measures in the studies of this category. Although good validity was found for SPT outputs from a smartphone application with camera tools (Kim et al. 2015), many unreliable results were found for smartphone 3-axes accelerometers (Silsupadol et al. 2020) and IMU SPT data acquisition (Brabandere 2020). This suggests that camera integrated systems have developed better for end user results. Although consumer grade technology is widely available, only Encephalog was commercially available as a complete solution for researchers gathering metrics of interest (Tchelet et al. 2019). This highlights that further progress is required for many of these fully remote and smartphone-based tools.

Interestingly, studies that used more than one system at one time (Cui et al; Koiler et al) revealed a focus for technology fusion applied to future research data collection as the technology improves. Both studies demonstrated the value of using smartphone application software for data filtering, processing and outputs

providing a successful, user-friendly tool for reduction of laboratory-based equipment. Cui et al. (2017) used portable EMG in conjunction with wearable technology to collect kinematic and kinetic data parameters. Though EMG data was collected, the main data used for functional parameters were force sensing and IMU units. Lack of EMG sensor data collection in study results also implies this parameter is only collected alongside other biomechanical parameters and less valuable information.

4.1.3 Insoles Platform

Most technologies in this category measured kinetic and SPT outcomes and took the form of an insole or device placed within a standard or customised shoe in common with widely available commercial products familiar to researchers. Generally, via force or pressure resistive sensors, when force is applied through the plantar surface of the foot (e.g. during stance phase of a gait cycle), a change in resistance allows phases of gait and pressure distribution on the plantar surface of the foot within a shoe/sock/insole to be calculated. This data is then used to determine SPT outputs and can be used in conjunction with kinematic based sensors and outputs (Amitrano et al. 2020; Chen et al. 2016; Cui et al. 2017; Haque et al. 2021) or camera-based technology (Bolaños et al, 2020; Bonnet et al. 2015). This kinetic data alongside kinematic joint angle data and could be paired with smartphone software, similar to other wearable/remote technologies reported (Yang et al., 2019).

Of specific note, are an experimental textile sock for analysis of gait and posture (Amitrano et al. 2020), that could overcome issues associated with insoles since they create an additional layer which can change the distribution of foot plantar loading (Oks et al. 2020). This would be more representative of laboratory-based activities that are usually undertaken barefoot. Also of note is SensFloor (SensFloor Gait, Future Shape GmbH, Germany) (Lanzola et al. 2020), a carpet product capable of recording basic SPT measures through identification of gait phases via the floor sensors which has shown good validity when compared to reference values. The carpet was identified as cost efficient and with good potential for patient rehabilitation monitoring, albeit limited to a defined environment.

The commercially available technology in this category reported were Loadsol (Renner and Queen, 2021) and OpenGo (Moticon Rego AG, Germany) (using a proprietary smartphone application) (He et al., 2019). Both are demonstrated as popular insole devices for gait data collection within the general market showing good usability features. Loadsol (Novel Electronics Inc. USA) insoles demonstrated high correlation values for vertical GRFs when compared to a gold standard instrumented treadmill. When used to detect gait impulse and loading rate, they could successfully identify various comparators such as age groups and degree of walking incline, thus providing an approachable technology for monitoring force and load information for patients' gait. OpenGo demonstrated effective data acquisition, possible use as a rehabilitative tool with auditory cues and knee adduction moment calculations, a well-known measure for OA disease progression (He et al.; Maly et al., 2013). Auditory feedback was administered via the smartphone application and demonstrated promising use for both rehabilitation training and patient monitoring within a home-based environment. It could also be integrated with other wearable/remote technology tools for rehabilitation and data collection.

4.1.4 Cameras

RGB-Depth cameras were found in a quarter of the results, many using the Microsoft Kinect skeletal tracker camera solution launched in 2010, with an upgraded version 2 launched in 2014. These cameras have the advantage of operating as a single camera system where multi-camera systems are not feasible (Albert et al.

2020), e.g., clinics, field test conditions and fitness centres, and they do not require body fixed components. Whilst widely used in research, Kinect has had mixed results in comparison with gold standard systems; showing limitations to SPT parameters and 3D kinematic accuracy (Xu et al. 2015; Guess et al. 2017; Xu et al. 2017; Vilas-Boas et al. 2019), but good degrees of accuracy for simple kinematic measures such as 3D ROM and movement velocity (Otte et al. 2016). If combined with other systems, accuracy may be improved (Bonnet and Venture 2015).

Marker-less motion capture software is growing in both research and industry settings and 'Theia 3D Marker-less' was found in this review as one of the prominent commercially available systems. By using the optical motion camera set-up, and thus limiting the remoteness of its use, the deep learning algorithm-based system, removes the need however for marker-based set-ups and increases the portability of its use. Though further testing is stated to be required to enable better sensitivities to environmental factors and subject characteristics, the promising comparably accurate results to marker-based motion capture, demonstrate its potential for improving feasibility and sample size of OA patient data collection.

Other commercially available camera and optical tracker components were found to give reliable results only for functional test outputs (Multi-Directional Reach Test, Timed Up and Go) (Moreno et al. 2017) and had limitations based on errors when compared to optical tracking systems (Niechwiej-Szwedo et al. 2018). Only 1 technology incorporating a depth camera was found to be commercially available. The Echo5D is described by the manufacturer Atlas5D (Lincoln, MA) as an ambient measurement system (AMS) comprising a single depth camera and bespoke software for use in the home. Although it was suitable for use in a defined environment, validated use was for a single metric - walking speed - specifically in an MS population (Bethoux et al. 2018), therefore, the use for an OA or other MSK clinical populations may be limited. Although all individual depth camera devices found in the results are commercially available, none, other than the Echo5D were identified as being available as a standalone system specifically for human movement measures. However, they offer adaptive potential for research and data extraction purposes, offering significant and growing potential for the OA researcher.

Both the Kinect and the Nintendo Wii systems were developed primarily as gaming technologies for the entertainment market and were subsequently recognised by researchers for their potential. The original Kinect system (V1 and V2) has now been retired, therefore, products incorporating it are not commercially available. Kinect V1 and V2 were superseded by the launch of the next generation AI Microsoft Azure Kinect sensor released in 2020. Azure Kinect has a suite of applications including the Bodytracking SDK pose estimation model of human movement focussed on non-gaming industries including healthcare, MSK diagnosis and exercise evaluation (Mangal and Tiwari 2021). The Azure Kinect has been reported as demonstrating improved results for spatial measures compared to the original Kinect. Good comparison validity measures were found for finger and thumb joint angles when compared to optical systems (Albert et al. 2020; Zhu et al. 2021) as well as full body tracking for joint angles during treadmill walking (Yeung et al. 2021). However, caution is required with camera viewing angles when using a range of depth sensors for kinematic gait measurements. Considering the limitations, depth cameras are useful as a portable motion capture tool but may still require a small defined environment.

4.2 Location / Application of Technology Use

Freedom to use the technologies in any environment or location and their ability to be applied for a variety of uses without specialist knowledge or support are fundamental to classifying the technologies as suitable for 'remote' use or 'mobile research'. Many of the technologies in the review results lacked a methodology or reference for real-life, real-time assessment of remote or non-laboratory use. Therefore, most were only described as hypothetically suitable for remote use and in some cases no method for remote use was suggested. Equally many studies lacked detail on how data would be recovered and analysed, e.g., in real time or via additional processing. Additional factors such as battery life, range of use, method of data recovery and analysis would also impact usability and availability of the data.

Very few (9%) of the technologies could be determined as fully remote with two-thirds (68%) classified as part remote and the remainder (23%) portable only (Fig. 4). 'Portable' technology offers OA researchers additional tools to use in community, clinic, or other settings outside of the traditional laboratory and may still offer new and more cost-effective ways of gathering kinetic and kinematic metrics than those currently available. Therefore, we can conclude that use of technology outside of the laboratory for OA research is both feasible and possible.

Most technologies identified as commercially available (Table 4) were identified as 'part remote' and measuring SPT parameters. This highlights that trained users (patients/researchers) have an increasing number of opportunities to collect real world data in a variety of settings and is likely to continue growing and developing. Although small, the identification of 'fully remote' technologies could offer researchers the potential to gain new insights into the lives of those with OA through the ability to collect data in an unrestricted and unobserved way, and potentially collection of data over a longer period, enabling emerging patterns to be analysed as opposed to one off laboratory visits.

4.3 Experimental Technologies

The results demonstrated a wide range of technologies under experimental investigation for the gathering of useful OA research data. Whilst some of these (commercially available products) were similar to the IMU or insole platforms, others suggested alternative remote approaches, e.g., a reliable self-measurement hand ROM tool using the Apple iPhone (Alford 2020) as well as a proposed ultrasonic sensor network system for convenient at home gait assessment (Ashhar et al. 2017). These systems are complimented by findings in other work advocating the use of non-contact, low impact sensing such as smartphone apps for the measurement of ankle ROM (Wang 2019) and pulsed Doppler radar (Impulse radio ultra-wide band) to understand human walking patterns (Rana et al. 2019).

It is likely that further rapid developments of smart wearable technologies, AI and other technologies will gain greater focus for gait research resulting in a paradigm shift to acquire complex data employing predictive analytics (Mohan et al. 2021). It is also highly likely that further advances in gaming technology (such as VR) will be better deployed for biomedical use (Bonnechere et al. 2016) leading to further advances in marker-less data capture.

4.4 Limitations of study

A narrative overview of identified technologies was the primary objective of the research, however, it would be beneficial to perform in-depth comparative analysis within technology type/metrics measured. Other

technologies that did not fall within the inclusion criteria, due to their size or operating requirements, may still be suitable for remote or community use. Most studies did not include an OA population, an aging population, or a population mixed across the socio-economic divide. Translation to an OA population may be essential for evaluation depending on the research requirements. Most studies did not evaluate intra-operator reliability which contributes to the feasibility of translation of remote technology for use with OA patients. This also affects technology usability, a critical element for successful use of remote technology in research (Lilien et al. 2019).

Quality scoring of technology could have considered advantages and disadvantages based on economic factors, research skills and usability, environmental feasibility technical specifications or cost, (and thus practical elements that may impact usability such as weight, size, battery life, operation range and user interface complexity). Equally no consideration was given to the nature of the data recorded and how this data could be accessed or harvested from the device, or the ease of analysis or interpretation of this data.

4.5 Further Research

Given the range of technology scoped, OA researchers would benefit from studying available evidence of technology for the specific parameters and environment necessary or conducting a pilot feasibility study. This could be incorporated into a larger quality scoring assessment and include inter and intra-operator reliability scoring. Increasing developments in portable-based technology will give rise to new opportunities for ‘in situ’ OA patient data collection and broaden the field for new approaches. Validity of the technology for the proposed purpose and enable impacts on both researchers and participants can then be better understood, managed, and mitigated.

5.0 Conclusion

A wide range of potential technologies are available for the OA researcher to use outside of a traditional laboratory-based environment, including some that are commercially available. Currently they are mostly limited to provision of gait SPT measures. Evidence suggests new emerging technologies under development will increase the choice and availability of technology solutions for OA researchers in the future. Marker-less motion capture is gaining particular traction in both research and industry settings and vision-based approaches with developing computational sensitivities likely to expand feasibility for OA patient data collection. Embracing the emergence of innovative technologies offers the potential to simplify methods, influence the targeted patient group and outputs, reduce the cost of and skills necessary for data collection, and widen the locations and environments in which data can be collected. Technology that can operate remotely will facilitate the gathering of objective data, a better understanding of real-world OA and its impact on the patient.

This research has identified several technologies that can support the OA researcher currently and can provide data of differing types and quality, with IMUs identified as the most prevalent technology type in use and most likely used for collection of SPT measures. Technology selection is only one consideration for the OA researcher, and further research to understand the impact on both researchers and participants, and the feasibility of operating research projects with remote technology is required.

Funding Declaration

This research was commissioned and funded by the EPSRC funded OATech Network Plus [EP/N027264/1]. The funders played no role in the design, collection, analysis, and interpretation of results or writing of manuscript.

Declarations

Competing interests: The authors declare no competing interests.

References

1. Abedtash, H. and Holden, R. J. 2017. Systematic review of the effectiveness of health-related behavioral interventions using portable activity sensing devices (PASDs). Journal of the American Medical Informatics Association 24(5), pp. 1002–1013. doi: 10.1093/jamia/ocx006
2. Albert, J. A., Owolabi, V., Gebel, A., Brahms, C. M., Granacher, U. and Arnrich, B. 2020. Evaluation of the Pose Tracking Performance of the Azure Kinect and Kinect v2 for Gait Analysis in Comparison with a Gold Standard: A Pilot Study. Sensors 20(18), p. 08.
3. Alford, S. L. 2020. Remote self-measurement of wrist range of motion performed on normal wrists by a minimally trained individual using the iPhone level application only demonstrated good reliability in measuring wrist flexion and extension. Journal of Hand Therapy 01, p. 01.
4. Allseits, E., Kim, K. J., Bennett, C., Gailey, R., Gaunaurd, I. and Agrawal, V. 2018. A novel method for estimating knee angle using two leg-mounted gyroscopes for continuous monitoring with mobile health devices. Sensors (Switzerland) 18(9), doi: 10.3390/s18092759
5. Amitrano, F., Coccia, A., Ricciardi, C., Donisi, L., Cesarelli, G., Capodaglio, E. M. and D'Addio, G. 2020. Design and Validation of an E-Textile-Based Wearable Sock for Remote Gait and Postural Assessment. Sensors 20(22), p. 23.
6. Ammann, K. R. et al. 2020. Human motion component and envelope characterization via wireless wearable sensors. BMC Biomedical Engineering 2, p. 3.
7. Aqueveque, P., Gómez, B., Saavedra, F., Canales, C., Contreras, S., Ortega-Bastidas, P. and Cano-De-La-Cuerda, R. 2020. Validation of a portable system for spatial-temporal gait parameters based on a single inertial measurement unit and a mobile application. European Journal of Translational Myology 30(2), pp. 268–276. doi: 10.4081/ejtm.2020.9002
8. Arthritis, V. 2021. *The State of Musculoskeletal health 2021. Arthritis and other musculoskeletal conditions in numbers*.
9. Ashhar, K., Cheong Boon, S. and Keng He, K. 2017. A wearable ultrasonic sensor network for analysis of bilateral gait symmetry. *Annual International Conference Of The IEEE Engineering In Medicine And Biology Society* 2017, pp. 4455–4458.
10. Bakker, J. P. et al. 2019. A systematic review of feasibility studies promoting the use of mobile technologies in clinical research. npj Digital Medicine 2(1), doi: 10.1038/s41746-019-0125-x
11. Bell, K. et al. 2019. Verification of a Portable Motion Tracking System for Remote Management of Physical Rehabilitation of the Knee. Sensors 19(5), p. 1021. doi: 10.3390/s19051021
12. Belsi, A., Papi, E. and Mcgregor, A. H. 2016. Impact of wearable technology on psychosocial factors of osteoarthritis management: a qualitative study. BMJ Open 6(2), p. e010064. doi: 10.1136/bmjopen-2015-

010064

13. Benson, L. C., Clermont, C. A., Bošnjak, E. and Ferber, R. 2018. The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review. Gait & Posture 63, pp. 124–138. doi: 10.1016/j.gaitpost.2018.04.047
14. Bethoux, F., Varsanik, J. S., Chevalier, T. W., Halpern, E. F., Stough, D. and Kimmel, Z. M. 2018. Walking speed measurement with an Ambient Measurement System (AMS) in patients with multiple sclerosis and walking impairment. Gait and Posture 61, pp. 393–397. doi: 10.1016/j.gaitpost.2018.01.033
15. Bonnechere, B., Jansen, B. and Van Sint Jan, S. 2016. Cost-effective (gaming) motion and balance devices for functional assessment: Need or hype? Journal of Biomechanics 49(13), pp. 2561–2565. doi: 10.1016/j.jbiomech.2016.07.011
16. Bonnet, V. and Venture, G. 2015. Fast Determination of the Planar Body Segment Inertial Parameters Using Affordable Sensors. IEEE Transactions on Neural Systems & Rehabilitation Engineering 23(4), pp. 628–635.
17. Brabandere, A. D. 2020. A machine learning approach to estimate hip and knee joint loading using a mobile phone-embedded IMU. Frontiers in Bioengineering & Biotechnology 8, doi: 10.3389/fbioe.2020.00320
18. Brodie, M. A. D. et al. 2016. Wearable pendant device monitoring using new wavelet-based methods shows daily life and laboratory gaits are different. Medical and Biological Engineering and Computing 54(4), pp. 663–674. doi: 10.1007/s11517-015-1357-9
19. Celik, Y., Stuart, S., Woo, W. L. and Godfrey, A. 2021. Gait analysis in neurological populations: Progression in the use of wearables. Medical Engineering and Physics 87, pp. 9–29. doi: 10.1016/j.medengphy.2020.11.005
20. CMAS. 2021. *Clinical Movement Analysis Society Standards version 15*.
21. Cudejko. 2021. Applications ofWearable Technology in a Real-Life Setting in People with Knee Osteoarthritis: A Systematic Scoping Review. Journal of Clinical Medicine,
22. Dobson, F., Hinman, R. S., Hall, M., Terwee, C. B., Roos, E. M. and Bennell, K. L. 2012. Measurement properties of performance-based measures to assess physical function in hip and knee osteoarthritis: a systematic review. Osteoarthritis Cartilage 20(12), pp. 1548–1562. doi: 10.1016/j.joca.2012.08.015
23. Drazan. 2021. Moving outside the lab: Markerless motion capture accurately quantifies sagittal plane kinematics during the vertical jump.
24. Elenko, E., Underwood, L. and Zohar, D. 2015. Defining digital medicine. Nature Biotechnology 33(5), pp. 456–461. doi: 10.1038/nbt.3222
25. Guess, T. M., Razu, S., Jahandar, A., Skubic, M. and Huo, Z. 2017. Comparison of 3D joint angles measured with the Kinect 2.0 skeletal tracker versus a marker-based motion capture system. Journal of Applied Biomechanics 33(2), pp. 176–181. doi: 10.1123/jab.2016-0107
26. Halilaj, E., Shin, S., Rapp, E. and Xiang, D. 2021. American society of biomechanics early career achievement award 2020: Toward portable and modular biomechanics labs: How video and IMU fusion will change gait analysis. Journal of Biomechanics 129, p. 110650. doi: 10.1016/j.jbiomech.2021.110650
27. He, J., Lippmann, K., Shakoor, N., Ferrigno, C. and Wimmer, M. A. 2019. Unsupervised gait retraining using a wireless pressure-detecting shoe insole. Gait and Posture 70, pp. 408–413. doi: 10.1016/j.gaitpost.2019.03.021

28. Hillel, I. et al. 2019. Is every-day walking in older adults more analogous to dual-task walking or to usual walking? Elucidating the gaps between gait performance in the lab and during 24/7 monitoring. European Review of Aging and Physical Activity 16(1), doi: 10.1186/s11556-019-0214-5
29. Horton. 2021. *Securing a positive health care technology legacy from COVID-19*. Foundation, T.H.
30. Kanko, R. M., Laende, E. K., Davis, E. M., Selbie, W. S. and Deluzio, K. J. 2021. Concurrent assessment of gait kinematics using marker-based and markerless motion capture. Journal of Biomechanics 127, p. 110665. doi: 10.1016/j.jbiomech.2021.110665
31. Kim, A., Kim, J., Rietdyk, S. and Ziaie, B. 2015. A wearable smartphone-enabled camera-based system for gait assessment. Gait & Posture 42(2), pp. 138–144.
32. Kluge, F. et al. 2021. Consensus based framework for digital mobility monitoring. PLoS ONE 16(8), p. e0256541. doi: 10.1371/journal.pone.0256541
33. Kluge, F. et al. 2018. Pre-operative sensor-based gait parameters predict functional outcome after total knee arthroplasty. Gait & Posture 66, pp. 194–200. doi: 10.1016/j.gaitpost.2018.08.026
34. Kobsar, D., Masood, Z., Khan, H., Khalil, N., Kiwan, M. Y., Ridd, S. and Tobis, M. 2020. Wearable inertial sensors for gait analysis in adults with osteoarthritis—a scoping review. Sensors (Switzerland) 20(24), pp. 1–24. doi: 10.3390/s20247143
35. Kressig, R. W. and Beauchet, O. 2006. Guidelines for clinical applications of spatio-temporal gait analysis in older adults. Aging Clinical and Experimental Research 18(2), pp. 174–176. doi: 10.1007/bf03327437
36. Lanzola, G. et al. 2020. Bringing spatiotemporal gait analysis into clinical practice: Instrument validation and pilot study of a commercial sensorized carpet. Computer Methods and Programs in Biomedicine 188, doi: 10.1016/j.cmpb.2019.105292
37. Latorre, J., Llorens, R., Colomer, C. and Alcaniz, M. 2018. Reliability and comparison of Kinect-based methods for estimating spatiotemporal gait parameters of healthy and post-stroke individuals. Journal of Biomechanics 72, pp. 268–273.
38. Lee, J., Shin, S. Y., Ghorpade, G., Akbas, T. and Sulzer, J. 2019. Sensitivity comparison of inertial to optical motion capture during gait: implications for tracking recovery. *IEEE International Conference on Rehabilitation Robotics* 2019, pp. 139–144.
39. Lefeber, N., Degelaen, M., Truyers, C., Safin, I. and Beckwee, D. 2019. Validity and Reproducibility of Inertial Physilog Sensors for Spatiotemporal Gait Analysis in Patients With Stroke. IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society 27(9), pp. 1865–1874. doi: 10.1109/TNSRE.2019.2930751
40. Lilien, C., Gasnier, E., Gidaro, T., Seferian, A., Grelet, M., Vissière, D. and Servais, L. 2019. Home-based monitor for gait and activity analysis. Journal of Visualized Experiments 2019(150), doi: 10.3791/59668
41. Mangal, N. K. and Tiwari, A. K. 2021. A review of the evolution of scientific literature on technology-assisted approaches using RGB-D sensors for musculoskeletal health monitoring. Computers in Biology and Medicine 132, doi: 10.1016/j.compbiomed.2021.104316
42. Mennan, T. H. a., Alastair Channon b, Mark Elliott c, Brian Johnstone d,, Timor Kadir e, J. L. f., Mandy Peffers g, Andrew Pitsillides h, Nidhi Sofat i,, Caroline Stewart a, F. E. W. j., Eleftheria Zeggini k, Cathy Holt l, Sally Roberts a,*, The OATech and Consortium, N. 2020. The use of technology in the subcategorisation of osteoarthritis: a Delphi

43. study approach. Osteoarthritis and Cartilage Open 2 (2020) 100081, doi: https://doi.org/10.1016/j.ocarto.2020.100081
44. Milosevic, B., Leardini, A. and Farella, E. 2020. Kinect and wearable inertial sensors for motor rehabilitation programs at home: State of the art and an experimental comparison. BioMedical Engineering Online 19(1), doi: 10.1186/s12938-020-00762-7
45. Mohan, D. M., Khandoker, A. H., Wasti, S. A., Ismail Ibrahim Ismail Alali, S., Jelinek, H. F. and Khalaf, K. 2021. Assessment Methods of Post-stroke Gait: A Scoping Review of Technology-Driven Approaches to Gait Characterization and Analysis. Frontiers in Neurology 12, doi: 10.3389/fneur.2021.650024
46. Moon, Y. et al. 2017. Monitoring gait in multiple sclerosis with novel wearable motion sensors. PLoS ONE 12(2), doi: 10.1371/journal.pone.0171346
47. Moreno, F. A., Merchan-Baeza, J. A., Gonzalez-Sanchez, M., Gonzalez-Jimenez, J. and Cuesta-Vargas, A. I. 2017. Experimental Validation of Depth Cameras for the Parameterization of Functional Balance of Patients in Clinical Tests. Sensors 17(2), p. 22.
48. Morgan, C. et al. 2020. Systematic Review Looking at the Use of Technology to Measure Free-Living Symptom and Activity Outcomes in Parkinson's Disease in the Home or a Home-like Environment. Journal of Parkinson's Disease 10(2), pp. 429–454. doi: 10.3233/JPD-191781
49. Muro-de-la-Herran, A., Garcia-Zapirain, B. and Mendez-Zorrilla, A. 2014. Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications. Sensors (Basel, Switzerland) 14(2), pp. 3362–3394. doi: 10.3390/s140203362
50. Nascimento, L. M. S. D., Bonfati, L. V., Freitas, M. L. B., Mendes Junior, J. J. A., Siqueira, H. V. and Stevan, S. L. 2020. Sensors and Systems for Physical Rehabilitation and Health Monitoring—A Review. Sensors 20(15), p. 4063. doi: 10.3390/s20154063
51. Niechwiej-Szwedo, E., Gonzalez, D., Nouredanesh, M. and Tung, J. 2018. Evaluation of the leap motion controller during the performance of visually-guided upper limb movements. PLoS ONE 13(3), doi: 10.1371/journal.pone.0193639
52. OARSI. 2016. *Osteoarthritis: A Serious Disease*.
53. Oks, A., Katashev, A., Eizentals, P., Rozenstoka, S. and Suna, D. 2020. Smart socks: new effective method of gait monitoring for systems with limited number of plantar sensors. Health and Technology 10(4), pp. 853–860. doi: 10.1007/s12553-020-00421-w
54. Otte, K., Kayser, B., Mansow-Model, S., Verrel, J., Paul, F., Brandt, A. U. and Schmitz-HÃ¼bsch, T. 2016. Accuracy and reliability of the kinect version 2 for clinical measurement of motor function. PLoS ONE 11(11), doi: 10.1371/journal.pone.0166532
55. Oubre, B., Daneault, J. F., Boyer, K., Kim, J. H., Jasim, M., Bonato, P. and Lee, S. I. 2020. A Simple Low-Cost Wearable Sensor for Long-Term Ambulatory Monitoring of Knee Joint Kinematics. IEEE Transactions on Biomedical Engineering 67(12), pp. 3483–3490. doi: 10.1109/TBME.2020.2988438
56. Papi, E., Belsi, A. and Mcgregor, A. H. 2015. A knee monitoring device and the preferences of patients living with osteoarthritis: a qualitative study. BMJ Open 5(9), p. e007980. doi: 10.1136/bmjopen-2015-007980
57. Peters, D. M. et al. 2021. Utilization of wearable technology to assess gait and mobility post-stroke: a systematic review. Journal of Neuroengineering & Rehabilitation 18(1), p. 67.

58. Peters, M. D. J. et al. 2020. Updated methodological guidance for the conduct of scoping reviews. JBI Evid Synth 18(10), pp. 2119–2126. doi: 10.11124/jbies-20-00167
59. Petraglia, F., Scarcella, L., Pedrazzi, G., Brancato, L., Puers, R. and Costantino, C. 2019. Inertial sensors versus standard systems in gait analysis: A systematic review and meta-analysis. European Journal of Physical and Rehabilitation Medicine 55(2), pp. 265–280. doi: 10.23736/S1973-9087.18.05306-6
60. Rana, S. P., Dey, M., Ghavami, M. and Dudley, S. 2019. Non-Contact Human Gait Identification Through IR-UWB Edge-Based Monitoring Sensor. IEEE Sensors Journal 19(20), pp. 9282–9293. doi: 10.1109/JSEN.2019.2926238
61. Ranavolo, A., Draicchio, F., Varrecchia, T., Silvetti, A. and Iavicoli, S. 2018. Wearable Monitoring Devices for Biomechanical Risk Assessment at Work: Current Status and Future Challenges—A Systematic Review. *International Journal of Environmental Research and Public Health* 15(9), p. 2001. doi: 10.3390/ijerph15092001
62. Renner, K. and Queen, R. 2021. Detection of age and gender differences in walking using mobile wearable sensors. Gait and Posture 87, pp. 59–64. doi: 10.1016/j.gaitpost.2021.04.017
63. Rudisch, J., Jöllenbeck, T., Vogt, L., Cordes, T., Klotzbier, T. J., Vogel, O. and Wollesen, B. 2021. Agreement and consistency of five different clinical gait analysis systems in the assessment of spatiotemporal gait parameters. Gait Posture 85, pp. 55–64. doi: 10.1016/j.gaitpost.2021.01.013
64. Sawle, L., Bull, A., Conaghan, P., Pitsillides, A., Rowe, P., Holt, C. and Network, O. 2017. The Osteoarthritis Technology Network Plus (OATech Network+): a multidisciplinary approach to improving patient utcomes. doi: https://doi.org/10.1016/j.physio.2017.11.062
65. Schafer, A. G. M., Zalpour, C., von Piekartz, H., Hall, T. M. and Paelke, V. 2018. The efficacy of electronic health-supported home exercise interventions for patients with osteoarthritis of the knee: systematic review. *Journal of Medical Internet Research 2018 Apr;20(4):e152*,
66. Silsupadol, P., Prupetkaew, P., Kamnardsiri, T. and Lugade, V. 2020. Smartphone-Based Assessment of Gait during Straight Walking, Turning, and Walking Speed Modulation in Laboratory and Free-Living Environments. IEEE Journal of Biomedical and Health Informatics 24(4), pp. 1188–1195. doi: 10.1109/JBHI.2019.2930091
67. Small, S. R., Bullock, G. S., Khalid, S., Barker, K., Trivella, M. and Price, A. J. 2019. Current clinical utilisation of wearable motion sensors for the assessment of outcome following knee arthroplasty: a scoping review. BMJ Open 9(12), p. e033832. doi: 10.1136/bmjopen-2019-033832
68. Sun, Z. et al. 2020. Skin-like Ultrasensitive Strain Sensor for Full-Range Detection of Human Health Monitoring. ACS Applied Materials and Interfaces 12(11), pp. 13287–13295. doi: 10.1021/acsami.9b21751
69. Takayanagi, N., Sudo, M., Yamashiro, Y., Lee, S., Kobayashi, Y., Niki, Y. and Shimada, H. 2019. Relationship between Daily and In-laboratory Gait Speed among Healthy Community-dwelling Older Adults. Scientific Reports 9(1), doi: 10.1038/s41598-019-39695-0
70. Tchelet, K., Stark-Inbar, A. and Yekutieli, Z. 2019. Pilot study of the encephalog smartphone application for gait analysis. Sensors (Switzerland) 19(23), doi: 10.3390/s19235179
71. Teufl, W., Lorenz, M., Miezal, M., Taetz, B., Fröhlich, M. and Bleser, G. 2018. Towards Inertial Sensor Based Mobile Gait Analysis: Event-Detection and Spatio-Temporal Parameters. Sensors 19(1), p. 38. doi: 10.3390/s19010038

72. Urbanek, J. K., Zipunnikov, V., Harris, T., Crainiceanu, C., Harezlak, J. and Glynn, N. W. 2018. Validation of Gait Characteristics Extracted from Raw Accelerometry during Walking Against Measures of Physical Function, Mobility, Fatigability, and Fitness. Journals of Gerontology - Series A Biological Sciences and Medical Sciences 73(5), pp. 676–681. doi: 10.1093/gerona/glx174
73. Van Helvoort, E. M. et al. 2021. Relationship between motion, using the GaitSmartTM system, and radiographic knee osteoarthritis: an explorative analysis in the IMI-APPROACH cohort. Rheumatology 60(8), pp. 3588–3597. doi: 10.1093/rheumatology/keaa809
74. Vilas-Boas, M. D. C., Choupina, H. M. P., Rocha, A. P., Fernandes, J. M. and Cunha, J. P. S. 2019. Full-body motion assessment: Concurrent validation of two body tracking depth sensors versus a gold standard system during gait. Journal of Biomechanics 87, pp. 189–196.
75. Vitaloni, M. et al. 2020. A patients' view of OA: the Global Osteoarthritis Patient Perception Survey (GOAPPS), a pilot study. BMC Musculoskeletal Disorders 21(1), p. 727. doi: 10.1186/s12891-020-03741-0
76. Walmsley, C. P., Williams, S. A., Grisbrook, T., Elliott, C., Imms, C. and Campbell, A. 2018. Measurement of Upper Limb Range of Motion Using Wearable Sensors: A Systematic Review. Sports Medicine - Open 4(1), doi: 10.1186/s40798-018-0167-7
77. Wang, K. 2019. Smartphone Applications for Assessing Ankle Range of Motion in Clinical Practice. doi: 10.1177/2473011419874779
78. Werner, C., Heldmann, P., Hummel, S., Bauknecht, L., Bauer, J. M. and Hauer, K. 2020. Concurrent validity, test-retest reliability, and sensitivity to change of a single body-fixed sensor for gait analysis during rollator-assisted walking in acute geriatric patients. Sensors (Switzerland) 20(17), pp. 1–18. doi: 10.3390/s20174866
79. Wren, T. A. L., Tucker, C. A., Rethlefsen, S. A., Gorton, G. E. and Õunpuu, S. 2020. Clinical efficacy of instrumented gait analysis: Systematic review 2020 update. Gait & Posture 80, pp. 274–279. doi: 10.1016/j.gaitpost.2020.05.031
80. Xu, X., McGorry, R. W., Chou, L. S., Lin, J. H. and Chang, C. C. 2015. Accuracy of the Microsoft Kinect for measuring gait parameters during treadmill walking. Gait & Posture 42(2), pp. 145–151.
81. Xu, X., Robertson, M., Chen, K. B., Lin, J. H. and McGorry, R. W. 2017. Using the Microsoft Kinectâ„¢ to assess 3-D shoulder kinematics during computer use. Applied Ergonomics 65, pp. 418–423. doi: 10.1016/j.apergo.2017.04.004
82. Yeung, L. F., Yang, Z., Cheng, K. C., Du, D. and Tong, R. K. 2021. Effects of camera viewing angles on tracking kinematic gait patterns using Azure Kinect, Kinect v2 and Orbbec Astra Pro v2. Gait & Posture 87, pp. 19–26.
83. Zhou, L., Fischer, E., Tunca, C., Brahms, C. M., Ersoy, C., Granacher, U. and Arnrich, B. 2020. How We Found Our IMU: Guidelines to IMU Selection and a Comparison of Seven IMUs for Pervasive Healthcare Applications. Sensors 20(15), p. 4090.
84. Zhu, M. et al. 2019. Self-Powered and Self-Functional Cotton Sock Using Piezoelectric and Triboelectric Hybrid Mechanism for Healthcare and Sports Monitoring. ACS Nano, doi: 10.1021/acsnano.8b08329
85. Zhu, Y., Lu, W., Gan, W. and Hou, W. 2021. A contactless method to measure real-time finger motion using depth-based pose estimation. Computers in Biology & Medicine 131, p. 104282.

86. Zügner, R., Tranberg, R., Timperley, J., Hodgins, D., Mohaddes, M. and Kärrholm, J. 2019. Validation of inertial measurement units with optical tracking system in patients operated with Total hip arthroplasty. BMC Musculoskeletal Disorders 20(1), doi: 10.1186/s12891-019-2416-4

Table 3

Table 3 is available in the Supplementary Files section.

Figures

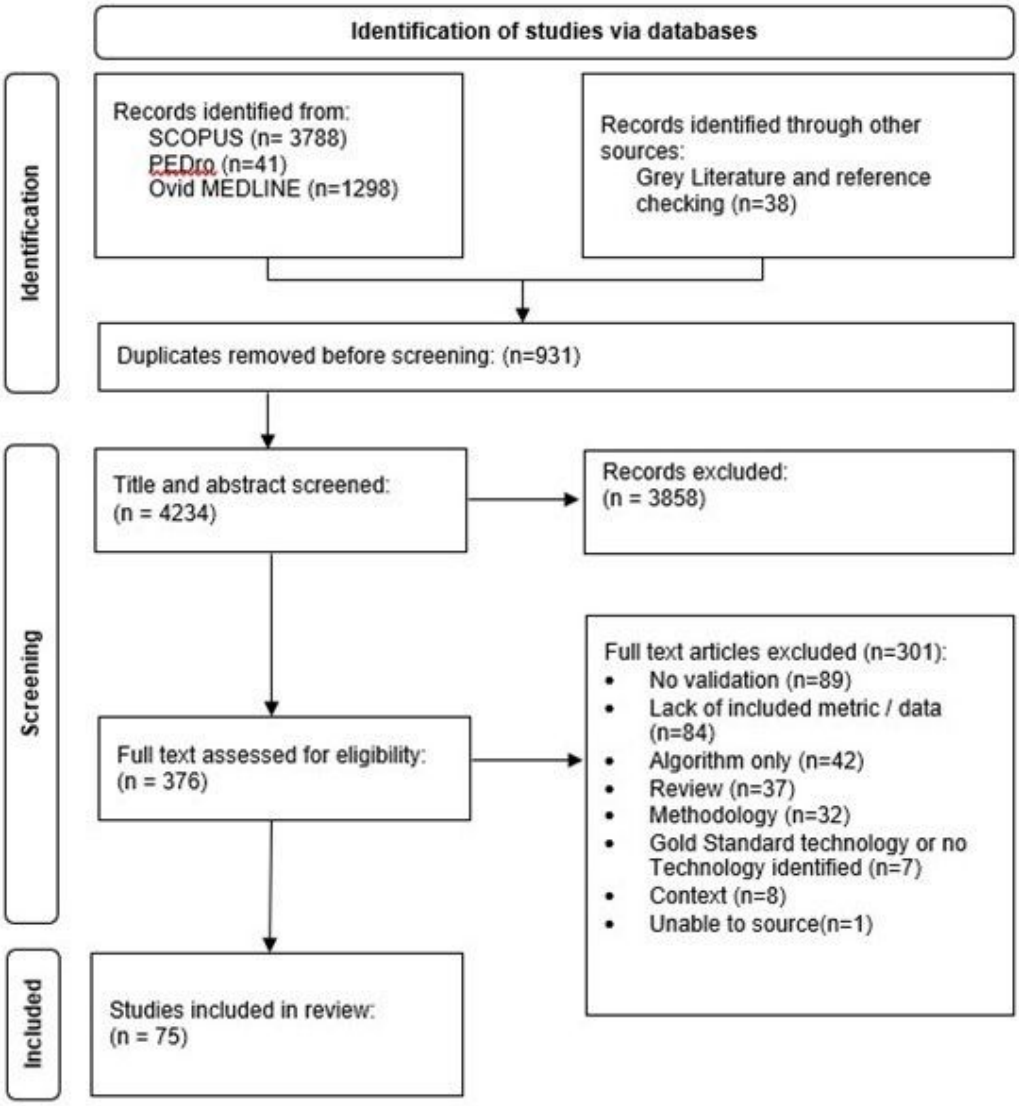

Figure 1

PRISMA Flow diagram of results.

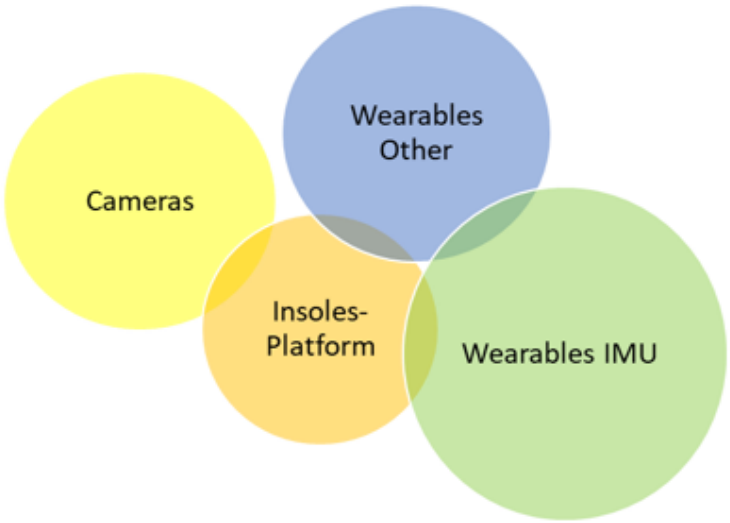

Figure 2

Technology results described by type category within a Venn diagram demonstrating several technologies measuring more than one category type (10.7%). IMU wearables were used the most in 25 technologies (30.1%), wearables of other varieties were used in 20 technologies (24.1%), cameras were used in 21 technologies (25.4%) and insoles or platforms were used in 17 technologies (20.5%).

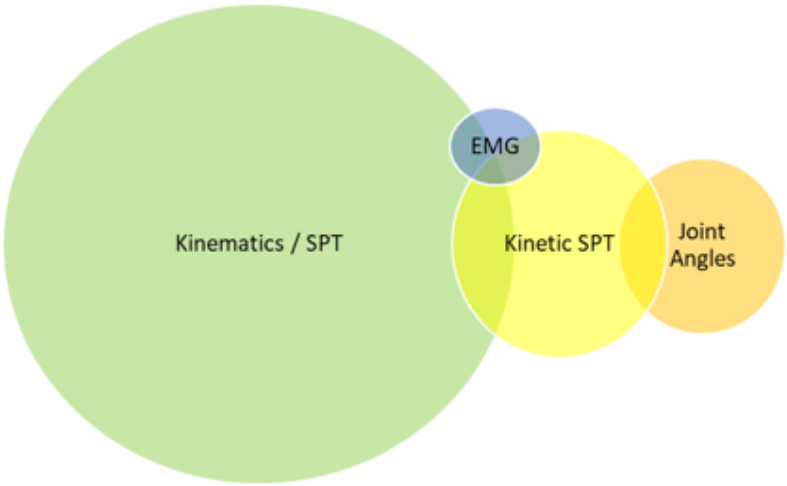

Figure 3

Technology results described by metrics measured within a Venn diagram demonstrating several technologies measuring more than one metric category (12%). Kinematics and SPT measures were used the most in 54 technologies (64.3%), kinetics and SPT measures were used in 16 technologies (19%), kinematics measuring joint angles and ROM were used in 13 technologies (15.5%) and electromyography measures were used in 2 technologies (2.4%).

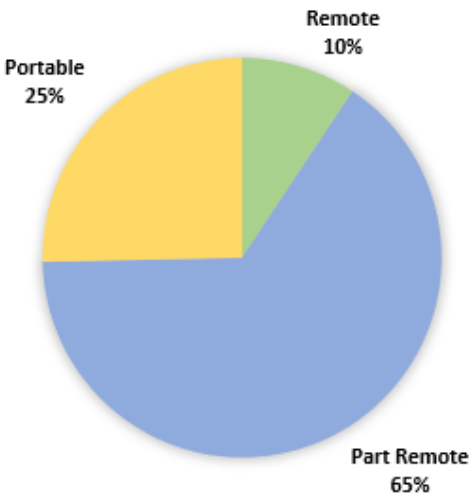

Figure 4

Technology results divided by application categories based on the criteria described in Table 2. Most technologies were categorised as part remote (65%), while 19 technologies categorised as portable (25%), and 7 technologies identified as fully remote (9%).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- supplementarymaterial24.06.2022.docx
- ExecSummary24.06.2022.docx
- Table3.docx