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Smartphone-Based Hand Function Assessment: A Systematic Review

Yan Fu, Yuxin Zhang, Bing Ye, Jessica Babineau, Yan Zhao, Zhengke Gao, Alex Mihailidis

Submitted to: Journal of Medical Internet Research
on: August 03, 2023

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Smartphone-Based Hand Function Assessment: A Systematic Review

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Abstract

Background: Hand function assessment heavily relies on specific task scenarios, making it challenging to ensure validity and reliability. Additionally, the wide range of assessment tools, and limited and expensive data recording, and analysis systems, further aggravate the issue. However, the ubiquitous smartphones in our daily life, they provide a promising opportunity to address these challenges. Implementing the built-in high-efficiency sensors in smartphones can be used as effective tools for hand function assessment.

Objective: This study aims to systematically evaluate existing studies on hand function evaluation using smartphones.

Methods: An extensive database search was conducted by an Information Specialist. Two reviewers independently screened all studies, with a third reviewer involved in resolving discrepancies. The final included studies were rated according to the Mixed Methods Appraisal Tool (MMAT). One reviewer extracted data on publication, demographic information, hand function types, sensors used for hand function assessment, and statistical or machine learning methods. Accuracy was checked by another reviewer. The data were synthesized and tabulated based on each of the four research questions.

Results: 46 studies were included. 11 types of hand dysfunction-related diseases were identified, such as Parkinson's Disease, wrist injury, stroke, and hand injury. Six types of hand dysfunctions were found including abnormal range of motion, tremors, bradykinesia, decline of fine-motor skills, hypokinesia, and non-specific dysfunction related to hand arthritis. Among all built-in smartphone sensors, the accelerometer was the most used, followed by the smartphone camera. Most studies used statistical methods for data processing, whereas machine learning (ML) algorithms were also applied for disease detection, disease severity evaluation, prediction, and feature aggregation. Limitations of the review include the nascent field of smartphone-based hand function assessment and the variability in literature quality.

Conclusions: This systematic review highlights the potential of smartphone-based hand function assessment. The review suggests that a smartphone is a promising tool in hand function evaluation without the constant involvement of therapists. ML is a conducive method to classify levels of hand dysfunction by smartphones. Future research could (1) explore a gold standard for smartphone-based hand function assessment; (2) take advantage of smartphones' multiple built-in sensors to assess hand function comprehensively; (3) focus on developing ML methods for processing collected smartphone data and (4) focus on real-time assessment during rehabilitation training.

(JMIR Preprints 03/08/2023:51564)
DOI: https://doi.org/10.2196/preprints.51564

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Abstract

Background: Hand function assessment heavily relies on specific task scenarios, making it challenging to ensure validity and reliability. Additionally, the wide range of assessment tools, limited and expensive data recording, and analysis systems, further aggravate the issue. However, smarphones provide a promising opportunity to address these challenges. Thus, implementing the built-in high-efficiency sensors in smartphones can be used as effective tools for hand function assessment.

Objective: This study aims to evaluate existing studies on hand function evaluation using smartphones.

*Methods: An*n Information Specialist searched 8 database on June 8, 2023. The search criteria include two major concepts: (1) smartphone/mobile phone or mHealth, and (2) hand function or function assessment. Searches were limited to English language, human studies, and excluded conference proceedings and trial register records. Two reviewers independently screened all studies, with a third reviewer involved in resolving discrepancies. The final included studies were rated according to the Mixed Methods Appraisal Tool. One reviewer extracted data on publication, demographic information, hand function types, sensors used for hand function assessment, and statistical or machine learning methods. Accuracy was checked by another reviewer. The data were synthesized and tabulated based on each of the research questions.

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Conclusion: This systematic review highlights the potential of smartphone-based hand function assessment. The review suggests that a smartphone is a promising tool in hand function evaluation. ML is a conducive method to classify levels of hand dysfunction. Future research could (1) explore a gold standard for smartphone-based hand function assessment; (2) take advantage of smartphones' multiple built-in sensors to assess hand function comprehensively; (3) focus on developing ML methods for processing collected smartphone data and (4) focus on real-time assessment during rehabilitation training. The limitation of the research are 1) The nascent nature of smartphone-based hand function assessment lead limited relevant literature, affecting the evidence's completeness and comprehensiveness. This can hinder supporting viewpoints and drawing conclusions. 2) The literature quality varies due to the exploratory nature of the topic, with potential inconsistencies and a lack of high-quality reference studies and meta-analyses.

Keywords: Hand function assessment; Smartphone-based sensing; rehabilitation; Digital health/mHealth

Introduction

Hand function assessment is crucial in determining the extent of functional loss in patients and the outcome of surgical and rehabilitative procedures. Subtle changes in hand function could be a good predictor for early detection of certain neuromuscular degeneration diseases such as Parkinson's

Disease (PD), which could help take preventive measures to reduce the severity of the illness [1]. However, most current hand assessments are conducted in a clinical context with the intensive involvement of rehabilitation professionals. The clinical evaluation requires frequent visits and long-duration treatment sessions [2]. Hand function is usually assessed using standard questionnaires, such as the Michigan Hand Outcome Questionnaire (MHQ), and Disability of the Arm, Shoulder, and Hand Index (DASH) [3]. These measurements are subjective and could result in different assessment results across different test scenarios and medical professionals [4]. Clinical outcomes based on a rating scale are often insensitive to subtle hand function changes, and unable to provide timely feedback [5]. As such, a hand assessment tool that can overcome the clinical assessment drawbacks of inconvenience, high cost, and imprecision for hand assessment [1, 5] and automatically evaluate hand function over time would benefit patients.

Smartphones are equipped with advanced technologies such as touchscreens, accelerometers, and gyroscopes, which can be utilized for measuring and evaluating hand function [6]. The application of smartphone in clinical hand dysfunction assessment can exploit built-in sensors (such as accelerometers and gyroscopes) to collect real-time hand movement data with convenience and low cost [7]. Smartphones can precisely monitor a patient's hand condition for dysfunction assessment by using Machine Learning (ML) and Artificial Intelligence (AI) algorithms to analyze the collected data [8]. Moreover, the smartphone-based hand dysfunction assessment can be designed according to clinical criteria to improve the system's reliability and validity [9–11]. Despite recent increased developments in smartphone-based hand function assessment [12, 13], no systematic reviews have been done to provide a holistic perspective on how smartphones can be applied to hand function assessment.

Although other technologies such as wrist-worn/finger-worn sensors, smartwatches, and specialized keyboards also show potential for automated hand function assessment. However, they typically focus on simple physiological data collection with limited data processing capabilities and display of basic information[14–16]. Whereas smartphones offer more extensive data acquisition, accurate data processing, and richer data display options, providing a more comprehensive technological solution [17, 18]. Moreover, considering the widespread availability and user-friendly nature of smartphones [19], directing research efforts toward smartphone-centric studies can enhance innovation and application possibilities. This approach not only aligns with the current prevalence of smartphones but also extends a broader scope for future technology transfer and development specific to hand function assessment. Therefore, focusing on smartphone research can lead to more innovation and application possibilities, offering a broader scope for future technology transfer and development. As such, the main goal of this review is to synthesize the present ways smartphones are applied in hand function assessment and the extent the hand function evaluation has been achieved using smartphones. It aims to explore the system development guidelines for the future application of smartphones in hand function assessment.

The research questions (RQs) are as follows:

1. What types of hand dysfunction are studied, and what assessment inventory tools are used?
2. How are smartphones applied in clinical practice in hand function assessment?
3. What sensors are integrated into smartphones to collect hand function data?
4. What statistics or machine learning algorithms are used for hand function assessment?

Research Methodology

The systematic review was reported according to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Multimedia Appendix 1).

Information Sources and Search Strategy

An information specialist (JB) developed and executed a comprehensive search strategy. The following electronic databases were searched: MEDLINE (R) ALL (Ovid), Embase and Embase Classic (Ovid), Cochrane Central Register of Controlled Trials (CENTRAL, Ovid), Scopus, Compendex (Engineering Village), INSPEC (Engineering Village), IEEE Xplore, and ACM Digital Library. The search strategy was first developed in MEDLINE ALL (Ovid) in consultation with the research team. Search terms were also sourced from a previously published review [20]. The search strategy was then translated into other databases.

Search strategies included the use of text words and subject headings related to two major concepts: (1) smartphone/mobile phone or mHealth, and (2) hand function or function assessment. Searches were limited to English language papers. When possible, searches were also limited to human studies, and excluded conference proceedings and trial register records. No date limits were applied. All searches were conducted on June 8, 2023. The full search strategies for each database are provided in Multimedia Appendix 2.

Study Selection

The studies were imported into Covidence after eliminating duplicates using Endnote. Title and abstract screening and full-text screening were completed by two researchers (YZ and YF) independently based on the same inclusion and exclusion criteria. Any disagreement was first discussed and solved by the two researchers. Otherwise, a third researcher (BY) was involved to ensure the agreement was reached.
The inclusion and exclusion criteria used for the screening process are presented in Table 1.
Table 1. The inclusion and exclusion criteria were used for the screening process.

	Inclusion Criteria	Exclusion Criteria
Paper Type		
Technology	Use of smartphone sensors	Not using a smartphone for hand function assessment
Study Focus	Hand function screening, including hand movement assessment, hand performance measurement	Health management, neurocognitive studies
Clinical Assessment	Measurement of motor function-related criteria such as grip strength, posture, and Degree of Freedom	Qualitative studies, non-peer-reviewed, non-academic studies
Study Design	Peer-reviewed academic studies	Systematic reviews, literature reviews, case reports, letters
Language		
	English	Non-English
Population		
	Human participants	Non-Human participants

The neurocognitive is evaluated independently in clinical hand assessment criteria [21].Therefore, the exclusion of neurocognitive studies in the review was made to focus specifically on aspects related to hand motor control and dysfunction. Although cognitive functions play a significant role in hand motor control, the primary aim of this review was to narrow its scope and focus on the specific factors directly related to the mechanics and dysfunction of the hand, with a particular focus on methods and techniques for utilizing smartphones in assessment. Neurocognitive research often involves specialized equipment and methods, such as neuroimaging techniques like fMRI or EEG, which may not be practical for assessing hand function in smartphone-related contexts.

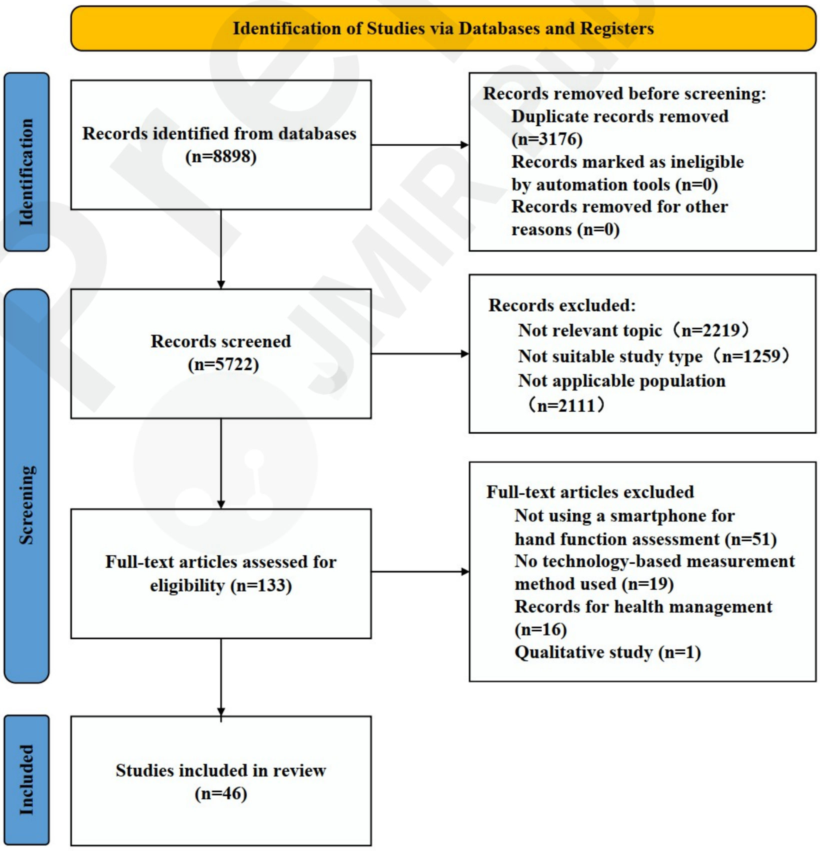
After the screening stage, the research quality of selected studies was evaluated by the Mixed Methods Appraisal Tool (MMAT), a tool designed for the systematic mixed research review evaluation phase[22]. The quality assessment was completed by one researcher and checked by a second researcher. The conflict was discussed between the two researchers and an agreement was reached.

Results

Overview

A total of 8898 records were retrieved from the search. After removing duplicates, 64.31% (5722/9516) of records were filtered at the title and abstract stage. In the first stage, 97.67% (5589/5722) of the records were removed. The remaining 2.32% (133/5722) articles underwent full-text screening. A total of 46 studies were included after both screening stages and included in the final review. Figure 1 presents the PRISMA [23] flow diagram. Multimedia Appendix 3 shows the included studies' evaluation based on the MMAT. In all, 46 studies were published after 2012, and 67% (31/46) of them were published between 2017 and 2023.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram illustrating the screening process for papers included in this study.



Study Characteristics

Fourteen studies (30%) recruited participants with hand dysfunction, seven studies (15%) only included healthy participants; and Twenty-three studies (50%) recruited both types of participants (see Table 2). The summarized smartphone specification is shown in Table 3. The age range was 21 to 91 years old for hand dysfunction patients, and 17 to 81 years old for healthy participants, the sample size varied from 1 to 1815.

Table 2. Characteristics of the studies (N=46)

	Reference
Participants	
Patients only	[9, 24–36]
Healthy participants only	[37–43]
Patients and healthy subjects	[10, 11, 29, 44–63]
N/A	[64, 65]
Gender	
Male only	[25, 37]
Female only	[66]
Male and female	[9–11, 26–28, 30, 31, 33–35, 39–42, 44, 45, 47, 48, 51–53, 56–60, 62–64]
N/A	[24, 29, 32, 36, 38, 43, 46, 49, 50, 54, 55, 61, 65]
Study design	
Quantitative descriptive	[9, 24–29, 31–44, 48, 49, 55, 64, 65]
Observation	[45–47, 50, 51, 56, 57, 59]
Non-randomized study	[10, 11, 25, 30, 38, 45–47, 50–54, 56–63, 66]
Case-control study	[66]
Study duration	
0-4min	[10, 28, 29, 31, 39, 59, 66]
10min	[40]
1.5hour	[51]
10 hours	[52]
1-4 weeks	[9, 26, 44, 56]
6-12 weeks	[47, 55, 58]
N/A	[11, 24, 25, 27, 30, 32–38, 41–43, 45, 46, 48–50, 53, 54, 56, 57, 60–65]
Sample size distribution	
0-32	[10, 24–26, 31–33, 37–39, 41, 44, 48, 56, 59, 65, 66]
33-64	[27, 28, 30, 35, 42, 43, 49, 50, 53, 57, 60, 62, 63]
65-95	[11, 34, 47, 52, 55]
96-126	[9, 46, 51, 64]
127-189	[40, 45]
190-220	N/A
221-252	[29]
253-598	N/A
599-629	[58]
630-1851	[36, 54, 61]

Table 3. The summary of smartphone specification

Study	Processing power	Operation system	Smartphone type	Sensor sampling rate	Camera resolution
Matera et al., 2016 [26]	N/A	Android	Nuans Neo Reloaded, HUAWEI GR5	N/A	N/A
Miyake et al., 2020 [24]	1.2 GHz dual-core processor	N/A	N/A	Accelerometer □ range±2g, 100 Hz□	N/A
Garcia-Magarino et al., 2016 [44]	N/A	Android	Samsung Galaxy Trend Plus smartphone	N/A	N/A
Bercht et al., 2012 [25]	N/A	iOS and Android 4.4.2	iPhone4S □ Samsung Galaxy S4 and a Google Nexus 5	N/A	N/A
Janarthanan et al., 2020 [39]	N/A	Android	LG Optimus G smartphones	N/A	N/A
Pan et al., 2015 [28]	N/A	iOS	iPhone	Accelerometer (100 Hz)	N/A
Orozco-Arroyave et al., 2020 [52]	N/A	Android	Android smartphone	Accelerometer (100 Hz)	N/A
Sarwat et al., 2021 [32]	N/A	N/A	N/A	N/A	N/A
Kostikis et al., 2015 [10]	N/A	Android	N/A	Accelerometer and gyroscope (20 Hz)	N/A
Lee et al., 2016 [45]	N/A	Android	Galaxy S3 mini, Android phone	N/A	N/A
Lipsmeier et al., 2018 [47]	N/A	Android	tablet	Accelerometer and gyroscope (66.6±10 Hz); magnetometer (66.6±7 Hz); microphone (44.1 kHz)	N/A
Sandison et al., 2020 [48]	N/A	N/A	N/A	N/A	N/A
Halic et al., 2014 [49]	N/A	iOS	iPhone 5	N/A	N/A

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Koyama et al., 2021 [30]	N/A	N/A	N/A	N/A	N/A
Chén et al., 2020 [55]	N/A	iOS	iPhone4	N/A	N/A
Arroyo-Gallego et al.,2017 [57]	N/A	Android 7.0	Huawei P9 Plus	Custom screen keyboard (1.2 GHz)	N/A
Pratap et al., 2020 [58]	N/A	N/A	Huawei Mate 9 Pro smartphone	N/A	N/A
Waddell et al., 2021 [59]	N/A	N/A	N/A	The app-touchscreen, accelerometer, and gyroscope (50 Hz)	N/A
Mousavi et al., 2020 [64]	N/A	Android 4.0	N/A	Mobile accelerometer software (100 Hz)	N/A
Lee et al., 2016 [62]	N/A	N/A	N/A	N/A	N/A
Hidaya et al., 2015 [66]	N/A	N/A	Huawei P10 Lite	N/A	N/A
Wang et al., 2016 [37]	N/A	N/A	N/A	N/A	N/A
Lee et al.,2018 [38]	N/A	Android	N/A	N/A	N/A
Iakovakis et al., 2019 [46]	N/A	iOS	iPhone XS Max	N/A	N/A
Modest et al., 2019 [50]	N/A	iOS	iPhone XS Max	N/A	N/A
Lendner et al., 2019 [40]	N/A	iOS	iPhone	N/A	N/A
Tian et al.,2019 [51]	N/A	Android	Samsung Galaxy S3 mini	N/A	N/A
Ge et al.,2020 [27]	N/A	Android	N/A	N/A	20 million pixels

Lee et al.,2016 [9]	N/A	Android	LG Optimus S smartphones	N/A	N/A
Reed et al., 2022 [29]	N/A	Android 5.0.	Motorola Moto G II	N/A	N/A
Williams et al., 2021 [31]	N/A	Android 2.2	HTC Desire smartphone	N/A	60 frames per second and 1920× 1080 pixel resolution
Gu et al., 2022 [53]	N/A	Android	Sony Xperia	N/A	image resolution: 1980× 1080 pixel
Gu et al., 2023 [41]	N/A	iOS	iPhone 5 or newer device	N/A	image resolution: 1980× 1081 pixel
Prince et al., 2018 [54]	N/A	Android	N/A	N/A	N/A
Arora et al., 2015 [56]	N/A	N/A	N/A	N/A	N/A
Kassavetis et al., 2015 [33]	N/A	N/A	Huawei Mate 9 Pro	Smartphone accelerometers (50 Hz)	N/A
Ienaga et al., 2022 [43]	N/A	N/A	N/A	N/A	N/A
Espinoza et al., 2016 [34]	N/A	iOS	iPhone SE	N/A	N/A
Chen et al., 2021 [55]	N/A	N/A	N/A	N/A	20 million pixels
Surangsrirat et al., 2022 [36]	N/A	iOS	iPhone	N/A	N/A
Williams et al., 2020 [60]	N/A	iOS and Android	iPhone 11 Pro Max	N/A	60 frames per second, 1920 × 1080 pixels
Williams et al., 2020 [11]	N/A	Android	N/A	N/A	N/A
Prince et al., 2018 [61]	N/A	Android	N/A	Smartphone app, screen, and	N/A

				accelerometer (100Hz)	
Santos et al., 2017 [63]	N/A	iOS	iPone 5	N/A	N/A
Porkodi et al., 2023 [42]	N/A	Android	N/A	N/A	2400 x 1080-pixel, 64 MP f/1.89
Akhbardeh et al., 2015 [65]	N/A	N/A	Sony xperia z1	N/A	20.7 mega pixel

RQ1: What types of hand dysfunction are studied, and what clinical hand assessment tools are used?

The hand dysfunctions discussed in the 46 articles were classified as an abnormal hand range of motion (ROM) (18 studies, 39%), hand tremor (15 studies, 33%), hand bradykinesia (9 studies, 20%), fine hand use decline (9 studies, 20%), hypokinesia (4 studies, 9%), and arthritis-related hand dysfunction (2 studies, 4%). 27 studies (59%) used clinical hand assessment tools in the study (Sees Table 4).

Table 4. The hand dysfunction type

Hand dysfunction	Reference
Abnormal Range of Motion	[24–27, 32, 35, 37–43, 48–50, 53, 63]
Tremor	[9, 10, 28, 31, 33, 36, 44, 47, 51, 52, 55, 56, 58, 61, 64]
Bradykinesia	[9, 11, 33, 36, 45, 47, 51, 60, 61]
Fine-Motor Skills Decline	[39, 46, 9, 52, 55, 57–59, 62]
Hypokinesia	[30, 32, 34, 66]
Hand arthritis-related hand dysfunction	[29, 65]

1) Abnormal hand ROM

ROM is to describe how far a joint or muscle can move [67]. The measurement of ROM can indicate joint impairments in patients or the efficacy of rehabilitation programs [67]. Nineteen (39%) studies focused on abnormal ROM, and 11 (23%) studies focused on wrist ROM, 10 (21%) focused on finger ROM. Smartphones were generally placed in the flexor carpi radialis (FCR), and extensor pollicis longus [25, 37, 40] to measure wrist ROM, while distal interphalangeal joint (DIPj), proximal interphalangeal joint (PIPj) to measure finger ROM [24, 25, 35, 37–39, 41, 48, 53]. Six related diseases including hand injured [24, 25, 37, 38, 42, 49, 63], wrist injured [26, 27, 40, 49, 50], and stroke [32, 37, 39, 48], after hand surgery [41, 43], flexor tendon injured [35], and nerve injured [53]. Most (13/19, 68%) showed that the smartphone-based measurement method had the same reliability as the conventional goniometer when evaluating the ROM of healthy people and patients.

2) Hand Tremor

Hand tremor is a rhythmic, involuntary movement (ie, regularly recurrent) and oscillatory (ie, rotating around a central plane) involving hand distal joints (eg, fingers and wrist)[68]. All papers focus on PD hand tremors except one for Multiple Sclerosis (MS). For PD hand tremor assessment,

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the acceleration and rotational velocity signals shake number, and intensity were collected during daily life activities [10, 28, 36, 44, 47, 52, 55, 64], and the number or accuracy of each tap was collected in the finger tapping activity of smartphone app [33, 51, 54, 56, 58]. The smartphone-based hand dysfunction shows satisfactory repeatability and validity measured against the Movement Disorder Society of Unified Parkinson's Disease Rating Scale (MDS-UPDRS-III) [28, 33, 36, 54, 56].

3) Hand Bradykinesia

Hand bradykinesia is characterized by slowness, reduced amplitude of movement, and sequence effect [69]. PD and MS were diseases related to hand bradykinesia. PD and MS bradykinesia were detected in touch gestures, including finger tapping [9, 11, 36, 45, 60, 61], and flick and pinch tactile behaviors [51], the number of tapping trials and finger positions were collected to assess bradykinesia in hands. Daily activities and finger-to-nose tests were performed when holding the smartphone [33, 47]. It is found that smartphones are comparable to conventional methods (MDS-UPDRS, MBRS) for assessing hand bradykinesia and may be useful in clinical practice [11, 33, 36, 60].

4) Fine Hand Use Decline

Fine hand use refers to movements created with the use of small muscles, such as using a pencil to draw [70]. Four diseases were mentioned: PD [9, 46, 52, 55, 57, 62], stroke [39], MS [58], and Huntington’s disease (HD) [59]. This hand dysfunction was assessed through smartphone screen interaction, such as playing games and typing activities [39]. Users' hold time (HT), flight time (FT), and pressure sequences during smartphone keystroke typing activity were used to quantify fine motor function [9, 46, 55, 57–59, 62]. Studies show that smartphone has the potential to detect PD symptoms from users’ typing activity, which facilitates the digital tools development for remote pathological symptom screening [39, 46, 52].

5) Hypokinesia

Hypokinesia is a decline in muscle strength that causes the muscle to not contract or move as it used to [71]. Three diseases related to this hand dysfunction: are stroke [32, 66], Carpal tunnel syndrome (CTS) [30], and hand arthritis [34]. Stroke patients were asked to perform gestures of grasping and floating [32, 66] with a sensor glove worn. CTS patients’ hand information like finger position and velocity were gained by playing a game [30]. Arthritis patients participated in power (Po), pinch (Pi), and tripod (T) grip tasks to capture grip measures [34]. These new technologies show high sensitivity and specificity for disease detection and self-assessment [30, 34].

6) Hand arthritis-related hand dysfunction

Arthritis is a common condition and is the most frequent cause of disability in American adults [65]. The most common form of arthritis is osteoarthritis (OA), followed by inflammatory arthritis (IA) [72]. A method of analyzing hand dysfunction related to hand arthritis involved capturing photographs of each patient’s hand. The results indicated that this approach could assist in the primary care, clinical assessment, and management of patients with hand arthritis [29].

The hand assessment tools consist of clinical scales and instruments (see Table 5). Clinical hand assessment tools were used for two purposes: task design (7 studies, 15%) and smartphone assessment outcome validation (25 studies, 54%), the rest papers did not mention the clinical tools (14/46, 30%). MDS-UPDRS is the most used clinical scale (15 studies, 32%), while a conventional goniometer was the most used instrument (10 studies, 21%) [9, 24, 35, 38, 40, 42, 43, 50, 53, 63]. Some studies utilized the MDS-UPDRS and the Alternative finger-tapping test (AFT) as reference tasks to set up experiment tasks. The effectiveness and reliability of smartphone-based assessment methods were validated by comparing the results with the MDS-UPDRS and manual goniometry.

Table 5. Clinical hand assessment tools are used

Clinical assessment tools			
Clinical scale	References	Clinical instrument	References
For task design			
MDS-UPDRS	[9–11]	AFT	[9, 54, 57, 61]
CAPSIT-PD	[45]	TTT	[9]
For outcome validation			
MDS-UPDRS	[28, 31, 33, 36, 38, 39, 45, 54, 56, 57, 59, 60]	Conventional Goniometer	[9, 24, 35, 38, 40, 42, 43, 50, 53, 63]
PDDS	[58]	Mechanical Tappers	[45]
Neuro-QoL	[58]	Accelerometer	[52]
UHDRS	[59]	Electronic digital caliper	[65]
tDisease Activity Score-28	[34]		
PDQ-8	[36]		
MBRS	[11]		
Tang criteria	[35]		

RQ2: How are smartphone-based hand assessment tools applied in clinical practice?

The smartphone-based hand assessment has been applied in four different ways. It has been used for function parameter measurement (i.e., wrist/finger ROM, hand strength), disease-related dysfunction early detection, real-time assessment during rehabilitation, and function assessment and rating (see Table 6).

Table 6. Functions of the smartphone-based hand assessment tools.

Application Setting	Task scenario	Reference
Measurement		
	Finger/wrist extension/flexion	[24–27, 35, 37–43, 50, 53]
	Finger Implement Squeeze, and Finger Forward Flexor Tendon Gliding	[25]
	A grip force tracking task	[34, 48]
	TTT	[9, 45]

	RAM, Tremor Tracker, and CIT	[9]
	Wrist pronation and supination	[63]
(Early) Detection		
	Daily activity	[44]
	Extended and Rest in MDS-UPDRS	[10, 55]
	Finger taping test	[46, 55–57, 61, 62]
	Daily motor active tests	[47]
	Flick, drag, pinch, and handwriting gestures	[51]
	Play a game	[30]
	Finger-to-nose test, pronation supination test arm-circles exercise	[28]
	Photographic capture of the patient's hands	[29, 65]
	Reaction time test	[56]
Real-time assessment during rehabilitation		
	Finger and wrist extension	[26, 37, 39]
	Wrist Flexion, Wrist extension, Finger Implement Squeeze, and Finger Forward Flexor Tendon Gliding	[25]
	A grip force tracking task	[48]
	Play a game	[39, 49]
	Grasping, pinching, and waving	[32]
	Hand grip and flat	[66]
Function level rating		
	Hanging gestures	[28, 31, 33]
	Finger-to-nose test	[33, 52, 58]
	Photographic capture of the patient's hands	[65]
	A grip force tracking task	[30]
	Extended and Rest in MDS-UPDRS	[29, 52, 54]
	Finger taping test	[11, 33, 36, 58–60]
	Hold the phone	[52]

Eighteen out of 46 studies (39%) focused on the measurement of hand function parameters such as wrist ROM [26, 27, 37, 40, 42, 43, 50, 63], finger ROM [24, 25, 35, 37–39, 48, 53], hand gesture [53], hand dexterity [9] or hand grip strength [34]. Hand grip strength measurement and hand dexterity are conducted on smartphones and shown to have good constancy with traditional measurement tools [16, 23, 38].

Fifteen out of 46 (33%) papers focused on dysfunction assessment for early disease detection. Dysfunction such as hand tremor (10/46, 22%), hand bradykinesia (3/46, 7%), fine hand use decline (5/46, 11%), hypokinesia (2/46, 4%) are used as biomarkers for certain disease like PD [10, 29, 30, 44, 46, 47, 51, 52, 55–57, 61, 62, 65], CTS [30] and hand arthritis [63, 65]. The detection exhibits high sensitivity and specificity, supporting personalized treatment plan adjustments and enabling early disease diagnosis and optimized management [62].

Fourteen out of 46 (30%) studies concentrate on rating hand dysfunction severity mostly in PD or MS-induced hand tremor (8/46, 17%), and bradykinesia (4/46, 9%). The findings demonstrate that smartphones can determine the degree to which the patient is affected by the disease rating the severity of both the disease and hand dysfunction [48,67,68].

Eight of 46 studies (17%) explored how the smartphone is applied for real-time hand function assessment during hand rehabilitation [25, 26, 32, 37, 39, 48, 49, 66]. Smartphones provide an interactive interface with guided exercises, therapeutic games, and performance feedback [26, 48]. The results of real-time assessment during the rehabilitation can help increase patients' motivation and interest, reduce discontinuity in the rehabilitation process, and lower treatment costs [25, 26, 32, 37, 39, 48, 49, 66].

RQ3: How are smartphones used to assess hand function?

The literature showed that smartphones had been used in four ways for hand function assessment: data collection (38 studies,82%), data display (17 studies,37%), data transmission (15 studies, 33%), and data processing (6 studies, 13%).

1) Data Collection

Data were mainly collected by the embedded smartphone sensors and/or smartphone app [44]. Accelerometers were mostly used (12/46, 26%), followed by smartphone cameras (11/46, 24%), gyroscopes [10, 40, 47, 55, 59], and goniometers [38, 50] (see Table 7). The smartphone app (16/46, 35%), some of them [30, 33, 45, 54, 56, 58, 59] is developed to work as a digital tapper to collect the number of trials and position of each tap during the TTT, and AFT task to detect hand use, hand tremor, bradykinesia or ROM. Accelerometers can collect rich information including angles and the rotational velocity vector of the finger [24, 26]. The sampling rate range of accelerometers is 20-100 Hz. By using a smartphone's camera, the patient's hand picture can be captured to extract information such as wrist/finger extension and flexion, allowing measurement of joint ROM or extension [35, 41, 43]. The camera resolution range is 1920x1080 pixels to 2400x1080 pixels.

Table 7. Built-in sensors involving data collection

Sensor and measurement	APP name	References
Accelerometers All angles of DIPj, PIPj, and MPj including the right/left, active/passive, and extensor/flexor positions	Google LLC.EHMROM	[24]
Still acceleration	Hand Trembling detector APP (HTrembAPP)	[44]
The acceleration vector and the rotational velocity vector	DNM	[15]
Accelerometer signal	Roche PD Mobile APP v1 (Roche, Basel, Switzerland), PD Dr, Apkinson, GEORGE®, mPower, mobile accelerometer software	[28, 33, 36, 52, 55, 59, 61, 64]
Orientation, velocity, and motion	HandRehab APP	[26]
Smartphone APP Number/time/velocity/position/consistency/amplitude/accuracy of each tap	SmT, DNM, mPower, Apkinson, elevateMS, ReHand, GEORGE®,HLTapper	[30, 33, 36, 45, 52, 54, 56–59, 61, 62]
150 test parameters	DNM	[9]
Kinetic tremor and dysmetria in movement	elevateMS	[58]

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Pronation and supination, felxion and extension	DNM, angulus APP	[42, 63]
Camera Movement and tremor	Did not use the APP	[27, 31]
Hand video	Did not use the APP	[11, 31, 60]
Hand picture	DNM	[29, 35, 41–43, 53, 65]
Joints' angles, key point's distance	Did not use the APP	[53]
Extension/flexion of the joint	Did not use the APP	[35, 41, 43]
Movement of finger	Did not use the APP	[41]
Tapping frequency/amplitude/speed/rhythm	Did not use the APP	[11, 60]
Gyroscope Gyroscope data in discrete time	DNM	[10]
Gyroscope signal	Roche PD Mobile Application v1 (Roche, Basel, Switzerland), GEORGE®	[47, 55, 59]
Height, rotation, slope, and acceleration.	Gyroscope	[40]
Goniometer Finger flexion at MCPj, PIPj, and DIPj, flexion angles of the finger	Goniometer	[38]
Wrist flexion, extension, supination, and pronation ROM	Compass app	[50]
Global Positioning System		
Orientation, velocity, and motion	HandRehab APP; newly created smartphone APPs	[26]
Microphone Voice	Roche PD Mobile APP v1	[47]
Pressure sensor Pressure-based Features	Custom Android APP, the name did not mention	[51]
Finger pressure	DNM	[49]
IMU IMU-based Features	Custom Android APP, the name did not mention	[51]

2) Data Display

Data display (17/46, 37%) including raw data display (12/46, 26%), visual instructions [25, 26, 28, 30, 37, 39, 49, 58, 59, 62], and information notification [10, 52]. Data were frequently displayed in text forms [48, 28, 44, 52, 55, 32, 34, 62] and graphics forms [24, 26, 37, 66]. The test details like date and patient information[26, 44, 48]were usually displayed for the display content. The display also reports assessment feedback in the form of results or scores [25, 48]. Real-time feedback includes hand motion data [28, 48] or finger posture of virtual 3D [26] and interactive game interfaces [39]. Additionally, the app can display text reminders for exercises [52] and notifications for hand tremor detection [10].

3) Data Transmission

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It describes how data are transmitted between smartphones and external devices (see Table 8). Due to limited data processing capacity, smartphones normally send data to other resources through Bluetooth, USB dongles, and Wi-Fi for data processing and storage [39, 45, 47]. Twelve studies transmitted the data to a cloud server through a unidirectional transfer, meaning data only flows in one direction. Among them, seven studies developed a smartphone app to receive the built-in sensor data [10, 26, 28, 32, 45, 47, 52], and the other five papers designed a smartphone app to receive the training data from external devices (i.e., gloves) [25, 39, 49, 57, 66]. Three papers reported that smartphones transmitted data with an external device via bidirectional communication [32, 48, 66], indicating smartphones can send and receive data in both directions. Two papers discussed data privacy and security and referred to Health Insurance Portability and Accountability Act (HIPAA) regulations [32].

Table 8. The data-transmit objects

Receiving objects	Reference
Remote server	
Computer	[10, 64]
Google Drive	[45]
Cloud storage facility	[47]
Cloud Computing	[28, 50]
Remote server	[32, 52, 57]
Physicians	[25, 26, 47, 49]
External device	
Glove	[32, 39, 49, 66]
HandMATE device	[39, 48]

4) Data Processing

It is to use smartphones as terminals to analyze, manipulate, and transform raw data into useful information or machine-readable content [39]. Six studies (13 %) used the smartphone app to process data [24–26, 32, 39, 44], and one study reported the smartphone processing power [24]. The smartphone processes motion data collected from built-in sensors and external devices. Data collected from built-in sensors like ulnar and radius deviations are converted into ROM, and total active motion (TAM) [24, 39, 44]. Data from external devices' sensors like flex-sensor signals, and electromyography (EMG) were transformed into flexion/extension angles (in degrees) [26, 32]. One paper extracted the features from EMG sensors and then fed them toML for further gesture recognition on smartphone apps [25].

5) Smartphones used as multi-functions

A total of 21 studies designed smartphones integrating more than one function mentioned above. The most frequent combination is using a smartphone for data transmission and data display [25, 26, 28, 32, 39, 48, 49, 52, 66] (see Table 9). Eight papers combined three or more functions [24–26, 28, 32, 39, 44, 52]. For example, in Bercht's study, the smartphone was designed to integrate processing capabilities, enabling real-time reception of game display information from the glove's flex sensor and then displayed on the smartphone screen after local data processing [25].

Table 9. Studies presented smartphones for multifunctional purposes.

Study	Data Collection	Data Processing	Data Transmission	Data Display
Matera et al., 2016	√	√	√	√

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[26]				
Miyake et al., 2020 [24]	√	√		√
Garcia-Magarino et al., 2016 [44]	√	√		√
Bercht et al., 2012 [25]		√	√	√
Janarthanan et al., 2020 [39]		√	√	√
Pan et al., 2015 [28]	√		√	√
Orozco-Arroyave et al., 2020[52]	√		√	√
Sarwat et al., 2021 [32]		√	√	√
Kostikis et al., 2015 [10]	√		√	
Lee et al., 2016 [45]	√		√	
Lipsmeier et al., 2018 [47]	√		√	
Sandison et al., 2020 [48]			√	√
Halic et al., 2014 [49]			√	√
Koyama et al., 2021 [30]	√			√
Chén et al., 2020 [52]	√			√
Arroyo-Gallego et al.,2017[57]	√			√
Pratap et al., 2020 [58]	√		√	
Waddell et al., 2021 [59]	√			√
Mousavi et al., 2020 [64]	√			√
Lee et al., 2016 [62]	√		√	
Hidaya et al., 2015 [66]	√			√

RQ4: What statistics or machine learning algorithms are used for hand function assessment?

Thirty-nine papers (85%) used statistical methods to process the hand motion data, including parameters such as tapping speed, error, and speed during smartphone screen interaction. Twenty (43%) papers applied ML to analyze the raw data or, statistical features. Seventeen (34%) papers used both two statistical and ML methods, while four papers (9%) used neither statistics nor machine learning (ML) for data analysis [37, 39, 40, 50].

Statistical Methods

There were 21 types of statistical methods to process six types of hand motion raw data (see Table 10). The most used method is summary statistics (23/46, 50%), followed by normalization (7/46, 15%), and Fourier transform (6/46, 13%).

Table 10. Studies classified by statistical methods.

Data Processed	Statistical Method	References
Data collected during the smartphone screen interaction (i.e.tapping speed, error, speed, path, pressure, and distance)	Pythagoras' theorem	[45]
	Normalization	[33, 51, 52, 57, 59, 61]
	Bootstrap multiple regression	[9]
	Summary statistics (min, max, mean, median, and SD)	[11, 30, 36, 45, 54, 56, 57, 60, 62]
	Akaike Information Criterion	[9]
	Fourier transform	[11, 33, 60]
Accelerometer values and rotational velocity vector	ObtainDirection	[44]
	ObtainAlpha	[44]
	Bandpass filter	[10, 59]
	Spectral analysis	[10]
	Fourier transform	[10, 28]
	Summary statistics (min, max, mean, median, and SD)	[34]
	Mass-univariate	[55]
	Feature-wise correlation test	[55]
	Regularization	[55]
	Butterworth high-pass filter	[33]
	EMD	[64]
Smartphone video/picture	Fourier transform	[31]
	Normalization	[65]
	Summary statistics (min, max, mean, median, and SD)	[41]
	One-hot encoding categorical and scaling numerical responses	[29]
	Savitzky-Golay filter	[11]
Initiating/terminating flexion/extension/ROM	RMS of error	[27, 32, 35, 42, 48]
FSR/IMU/pressure sensor signals	Otsu's11 binarization	[43]
	RMS of error	[48]
	Summary statistics (min, max, mean, median, and SD)	[37, 32]
	SMA Filtering	[66]
Variables for model prediction (i.e. age, gender, occupation)	Linear mixed models	[40]
	Multiple linear regression	[9]

Machine Learning Methods

Sixteen types of ML methods were identified (see Table 11). They were applied for five purposes: disease detection, /disease severity evaluation, disease prediction, and feature aggregation. Support Vector Machines (SVM) is the most used ML method [10, 28, 51, 53, 57, 60, 64]. The input features of SVM were preprocessed acceleration signals such as the sums of squared magnitudes [10] and path/time-based features [51]. Tian et al [41] reported SVM as a reliable ML for early PD detection and multivariate classification with 0.89/0.88 sensitivity/specificity. Gu et al [53] report the highest gesture classification accuracy=1, with 1/1 sensitivity/specificity.

Five studies applied logistic regression for disease severity classification and prediction, and hand gesture discrimination [32, 55, 57, 60, 61]. The spatiotemporal features from the pixel coordinate data during finger tapping and accelerometer waveforms were the input of this ML. Logistic regression shows an average accuracy=88.50% ± 8.03% (Grasp), 83.00% ± 10.90% (pinch), 86.50% ± 12.57% (wave) [32], and accuracy=0.61, AUC=0.59 in PD prediction [60].

Three papers [29, 46, 61] exploit CNN to classify PD from healthy control based on hold time (HT), flight time (FT), and pressure sequences [46]. CNN exploits the finger-tapping rate data for PD severity identification with AUC=0.64 and accuracy=0.62 [61]. It also works as the base layer for training two image pre-processing models and discriminant PD tremors with 95% agreement with the accelerometer [29].

Seven studies [10, 32, 51, 53, 55, 57, 60] compared the classification performance of different ML algorithms. For example, Kostikis et al. applied DT, NB, C4.5DT, and a bagged ensemble of decision trees (BagDT) for identifying PD from healthy subjects based on PD hand tremor features. BagDT performed better than other classifiers, with an accuracy of 0.90 for the healthy group 0.82 for the PD group, and the AUC= 0.94 [10].

Table 11. Studies classified by machine learning algorithms

ML	Feature	Validity & Accuracy	Reference
SVM			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: sensitivity =0.56, specificity = 1	[10]
	Path-based, Time-based, Pressure-based, IMU-based Features, Additional Features for Handwriting Gestures and Pinch Gestures	From healthy controls: sensitivity=0.89 and specificity=0.88	[51]
	The total/peak/fraction power, average acceleration of the motion data	PD hand resting tremor detection: sensitivity=0.77, accuracy = 0.82	[28]
	Angle of fingers' MCPj,PIPj,DIPj,CMCj,webspace,etc	Highest gesture classification accuracy=1, sensitivity=1, specificity=1	[53]
	SFS to select the best feature from the mean, SD, skewness, etc from accelerometer signals	Identify tremor activity with the highest accuracy=0.91, specificity=0.90, sensitivity=0.90	[64]
	Touchscreen typing features: covariance, skewness, and	Aggregate the typing feature with AUC=0.88 (Linear-SVM)	[57]

	kurtosis analysis of the timing information		
	Tapping frequency, amplitude, energy spectral density, Peak-to-peak variability	Predicting Parkinson’s diagnosis with accuracu=0.63, AUC=0.60 (Linear-SVM)	[60]
	Tapping frequency, amplitude, energy spectral density, Peak-to-peak variability	Predicting Parkinson’s diagnosis with accuracy=0.69, AUC=0.68 (SVM-RBF)	[60]
Logistic Regression			
	The mean, RMS, SMA, and standard deviation for each axis of the accelerometer and gyroscope	Assess patient performance with average accuracy=88.50% ± 8.03% (Grasp), 83.00% ± 10.90% (pinch), 86.50% ± 12.57% (wave)	[32]
	Touchscreen typing features: covariance, skewness, and kurtosis analysis of the timing information	Aggregate the typing feature with AUC=0.87	[57]
	Tapping frequency, amplitude, energy spectral density, Peak-to-peak variability	Predicting Parkinson’s diagnosis with accuracy=0.61, AUC=0.59	[60]
	13 spatiotemporal features from the pixel coordinate data about speed, rhythm, accuracy, and fatigue, 28 features from three accelerometer waveforms, frequency, and temporal domains	Classify PD severity with AUC=63.1 ± 2.11, accuracy=59.5 ± 0.96	[61]
	Features selected according to formulas and parameters	Identify PD patients from healthy subjects: Accuracy=0.94, Sensitivity=0.95 and Specificity =0.94 (Multivariate Logistic Regression)	[55]
CNN			
	Four statistical features in total from hold time (HT), flight time (FT), and pressure sequences	Classification of PD and healthy control: In-the-clinic, mean performance=0.89, sensitivity=0.79, and specificity=0.79; In-the-wild, mean performance=0.79, sensitivity=0.74, and specificity=0.78	[46]
	12 features like sex, age, duration of symptom, etc	Discriminant PD tremor with 95% agreement with accelerometer	[29]
	Raw data of finger-tapping	Classify PD severity with AUC=63.5 ± 1.56, accuracy=62.1 ± 0.95	[61]
RF			
	Angle of fingers' MCPj,PIPj,DIPj,CMCj,webspace,etc	Highest gesture classification accuracy=1, ensitivity=1 and specificity=1	[53]

	mean, standard deviation, and median acceleration	In discriminating participants with PD from controls, sensitivity=0. 96 (SD 2%) and specificity = 0.97	[56]
	13 spatiotemporal features from the pixel coordinate data about speed, rhythm, accuracy, and fatigue, 28 features from three accelerometer waveforms, frequency, and temporal domains	classify PD severity with AUC=64.1 ± 1.08, accuracy=60.2 ± 1.56	[61]
Linear Regression			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: sensitivity=0.74 and Specificity=1	[10]
	Angle of fingers' MCPj,PIPj,DIPj,CMCj,webspace,etc	Highest gesture classification accuracy=1, ensitivity=1 and specificity=1	[53]
AdaBoost			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: Sensitivity=0.83 and Specificity=0.85	[34]
	Touchscreen typing features: covariance, skewness, and kurtosis analysis of the data timing information	Aggregate the typing feature with AUC=0.82	[57]
KNN			
	Time domain: the signal length, mean value, RMS value, number of vertices, and number of baseline crosses; Frequency domain: fundamental frequency, region length, and Fourier variance.	Validated with self-defined hand gesture performance classification standards with an accuracy of over 95%	[25]
NB			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: Sensitivity =0.56% and Specificity =1	[10]
	Tapping frequency, amplitude, energy spectral density, Peak-to-peak variability	Predicting Parkinson’s diagnosis with accuracu=0.69, AUC=0.70	[60]
XGBoost			
	Features selected according to formulas and parameters	Identify PD patients from healthy subjects: Accuracy=0.81, Sensitivity=0.83, and Specificity =0.9	[55]

	The mean, RMS, SMA, and standard deviation for each axis of the accelerometer and gyroscope	Assess patient performance with average accuracy=88.00% ± 9.88% (Grasp), 83.50% ± 7.74% (pinch), 82.00% ± 14.71% (wave)	[32]
C4.5 DT			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: Sensitivity=0.83 and Specificity =0.75	[10]
BagDT			
	Magα, magω, sdα, mAmpω	Distinguish the PD patient from the healthy subject: Sensitivity=0.82 and Specificity =0.90	[10]
DT			
	Magα, magω, sdα, mAmpω	Distinguish PD (82%) and healthy people (90%)	[10]
HAR			
	(1) Sustained phonation: MFCC2; (2) Rest tremor: skewness; (3) Postural tremor: total power; (4) Finger tapping; (5) Balance: mean velocity; (6) Gait: turn speed	Unlabeled PD activity test data: PD balance activity test: 99.5%; gait activity test 96.9% Distinguish between resting and gait activities: 98%;	[47]
Anomaly detection and an autoencoder			
	The position/time/ velocity of the thumb movement	Participants with and without CTS classified with sensitivity=0.94, specificity=0.67, AUC = 0.86	[30]
Elastic-net			
	Features selected according to formulas and parameters	Identify PD patients from healthy subjects: Accuracy=1, Sensitivity=0.95, and Specificity =1	[55]
DNN			
	13 spatiotemporal features from the pixel coordinate data: speed, rhythm, accuracy, and fatigue, 28 features from three accelerometer waveforms, frequency and temporal domains	Classify PD severity with AUC=65.7 ± 1.05, accuracy=61.2 ± 1.07	[61]

Discussions

To the best of our knowledge, this is the first systematic review of smartphone-based technologies' primary design ideas and development for hand function assessment using smartphones.

RQ1: What types of hand dysfunction are studied, and what assessment inventory tools are used?

In the literature, smartphones only assessed six types of hand dysfunction - abnormal ROM, tremor, bradykinesia, fine-motor skills decline, hypokinesia, and hand arthritis-related hand dysfunction. The reason might be that smartphones are limited in capturing the complexity and variety of hand movements to measure all aspects of clinically relevant hand functions [75]. Other types of hand dysfunction like abnormal ROM, decreased grip strength, altered sensation, and impaired coordination are important biomarkers clinically, requiring future development of smartphones to collect related parameters [76].

ROM is a critical and objective measurement that can reflect various diseases such as arthritis, trauma, or stroke [77]. Abnormal ROM is the most studied smartphone-based hand function assessment [24–27, 32, 37–43, 48–50, 53, 55, 63], indicating the advantages of smartphones in obtaining ROM parameters. Therefore, it is worth further smartphone development for better accuracy and reliability. With the advancement of built-in accelerometers and gyroscopes in smartphones, capturing and analyzing hand ROM data has become more accessible [77, 78]. Furthermore, it can accurately measure both dynamic and static ROM, providing good potential for long-term monitoring even without the presence of professionals [27].

PD is the most studied disease that causes hand dysfunction. PD could cause multiple hand dysfunctions such as tremors [9, 10, 44, 47, 51], bradykinesia [9, 45, 47, 51], abnormal ROM [37, 39, 48], and fine hand use decline [46]. It provides evidence that smartphones have the potential to provide a comprehensive assessment platform for multiple hand dysfunctions [9, 44–47].

In addition, chronic neurodegenerative diseases, such as PD, exhibit progressive symptoms that require continuous monitoring [7]. However, existing clinical assessment tools, such as MDS-UPDRS, tend to be subjective, time-constrained, and time-consuming [79]. Smartphone apps could exploit the multiple built-in sensors to detect changes indicative of the disease progression or treatment response [80–84], indicating smartphones can be prosperous tools for managing chronic hand dysfunction in the long run.

Above all, for a reliable clinical application of hand dysfunction assessment, the following should be emphasized:

1) Gold standards should be established and validated, specific to the smartphone as an assessment platform.

2) Smartphone assessment should be able to be customized according to an individual's condition and rehabilitation expectations [85];

3) Smartphone assessment procedures and tasks should adhere to the operational specifications of the clinical assessment criteria [2, 86];

4) An individualized rehabilitation plan can be generated out of the assessment and evaluated in real-time pace to monitor the individual's rehabilitation progress.

RQ2: How are smartphones applied in clinical practice in hand function?

Real-time assessment during hand rehabilitation is beneficial in the clinic because it allows modification of the rehabilitation tasks and goals according to an individual's specific needs and ongoing recovery progress [87]. In our review, studies on real-time smartphone-based assessment were primarily conducted between 2016 and 2022, indicating an emerging trend focusing on real-time hand assessment. The potential technical challenge may lie in identifying the best sensor configuration and feature extraction for hand function assessment [6,86].

Early detection of a degenerative disease through hand assessment is important because it can help slow down further disease progression [88]. The reviewed literature discusses conditions like PD, and CTS [34, 36, 37]. Future work could utilize smartphones as biomarker acquisition to monitor disease-relevant physiological, and behavioral symptoms and provide personalized rehabilitation guidance [89–91]. The use of smartphones as biomarkers offers advantages including portability, accessibility, affordability, non-invasiveness, and continuous monitoring, benefiting both patients and clinicians [92]. However, challenges exist in terms of data quality, reliability, and privacy concerns [93].

RQ3: How smartphones are used to assess hand function?

The smartphone was mostly used in data collection, with more sensors embedded in smartphones, richer and more dimensional data can be collected for function measurement. For example, the camera resolution of the smartphone's built-in camera is between 1920x1080 and 2400x1080 pixels, which is higher than the commonly used camera resolution in clinical settings, which typically ranges from 1280x720 to 1920x1080 pixels [8]. Compared to smartwatches and ring-shaped sensors, smartphones are more indispensable in people's daily lives, making them an easily available assessment tool and requiring no extra investment like others [94]. While webcams provide high resolution and frame rates, they rely on a stable internet connection and can potentially raise privacy and security concerns [95]. In comparison, the smartphone can collect data offline and protect the patient’s privacy by encrypting data, anonymizing personal information, and storing data locally [42]. This also shows that smartphones, as general-purpose devices, do not require excessive hardware requirements at low cost and are easy to access. Smartwatches and wearables usually feature multiple sensors similar to those found in smartphones, allowing for the collection of hand motion and physiological data with real-time feedback. However, their functionality is confined by a fixed position of the body, resulting in the limited scope of data collection [14]. In contrast, smartphones, being portable devices, are not constrained by fixed positions, granting convenience and flexibility for hand dysfunction assessment. Ring-shaped sensors offer high precision and accuracy and provide real-time data. However, their use may be limited due to comfort and portability constraints [16]. Smartphones are equipped with data processing modules, which can analyze and process data in real time providing better accuracy at the same cost [96]. In terms of user experience, as a more familiar product, smartphones reduce the users' learning cost and provide a more convenient, personalized, and friendly hand dysfunction evaluation experience, which helps to improve user participation and satisfaction [19]. However, one of the weaknesses of using a smartphone for data collection may be data errors or biases due to the smartphone user's lack of training, supervision, and quality control [97].

Using smartphones for data processing was the least mentioned in the studies [24–26, 32, 39, 44]. The benefits of smartphone data processing are manifold, including mobility, real-time processing, and interactive nature [98]. This empowers users to access and process data anytime, receive real-time feedback, and seamlessly interact with their smartphones, regardless of location [99]. Despite the advantages, there are also obstacles to overcome, including short battery life, limited storage capacity, and weak processing power [100]. Therefore, in our reviewed studies, most research focused on wireless transmitting data to computers or the cloud for subsequent data processing [10, 39, 47, 49]. This approach would allow for efficient data management and processing without consuming limited storage space on the smartphone [10] (See Figure 2).

In this review, seven studies (15%) exclusively involved healthy participants, while twenty-three studies (50%) recruited both patients and healthy participants. Consequently, 65% of studies included healthy participants, marking a noteworthy finding. In smartphone-based hand dysfunction assessment, incorporating baseline data from healthy participants is important for several reasons [37–43]. First, a standard reference range is typically derived from data collected from healthy participants, which could enable a more precise evaluation of a patient’s hand dysfunction. By comparing the hand function of patients to that of healthy participants, potential abnormalities can be identified more effectively, assisting in the accurate diagnosis of issues and facilitating the implementation of appropriate treatments [10, 11, 29, 44–63]. Second, during the rehabilitation process, the patient's recovery progress and improvement can be quantified by comparing it with health data [48, 49]. The effectiveness of treatment can be more accurately assessed and rehabilitation protocols could be adjusted for better outcomes. Third, establishing a normal reference range of healthy participants, including different ages, gender, and demographic characteristics. A broader set of data is available, ensuring that assessments are not limited to a specific group and can cover a broader population, resulting in a complete and more comprehensive understanding of hand function assessment [101].

In summary, remote assessment platforms have been developed for a wide range of users, including professionals, caregivers, and patients [2, 10]. However, certain aspects need to be considered when using smartphones for hand assessment. They are as follows: [28, 102–104]:
1) Establishing standardized data formats is of utmost importance to ensure compatibility and consistency in data analysis. Inconsistent data formats can pose challenges in data analysis, making it difficult to compare and analyze data obtained from various smartphones;
2) To ensure the robustness of smartphone processors or network connections. The effectiveness of the smartphone processor and network can impact the frequency of data updates, which may result in delays when acquiring and displaying real-time data.
3) To consider privacy and security. It is important to prioritize data security and privacy by implementing app-appropriate encryption measures during data transmission to mitigate potential ethical and legal issues and ensure compliance with relevant data protection regulations.

Figure 2. The primary design ideas for the development of smartphone-based hand function assessment technology.

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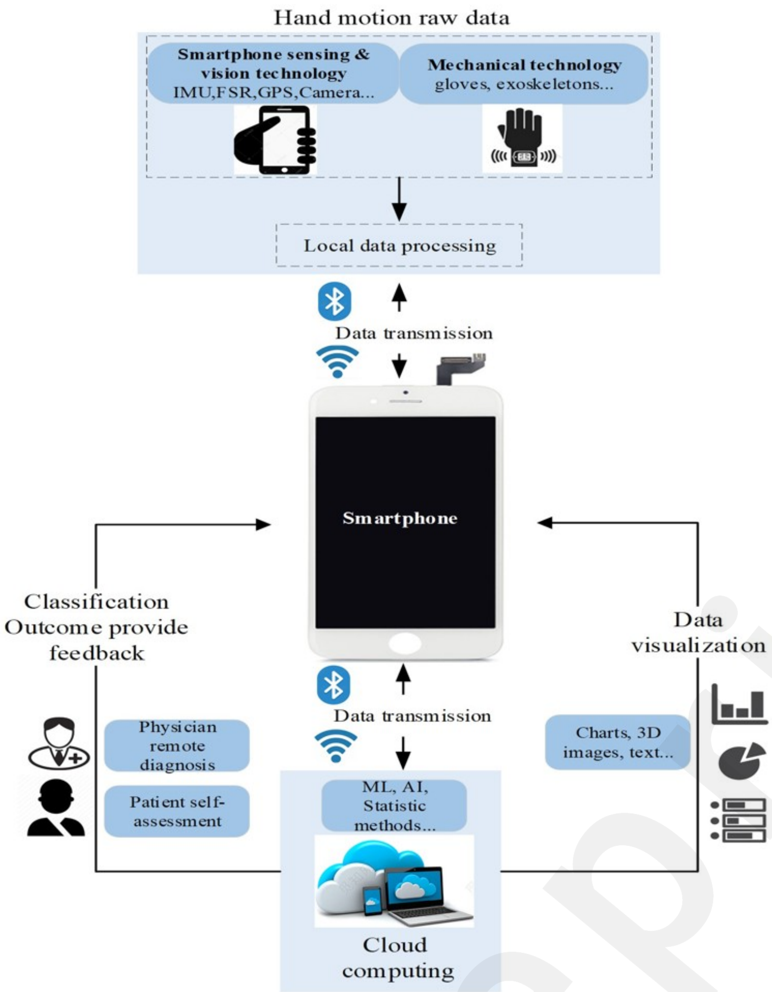

RQ4: What statistics or machine learning algorithms are used for hand function assessment?

Statistical methods (39/46, 85%) are more commonly used than ML (20/46, 43%), the most commonly used statistical method is summary statistics, such as mean, and SD. Summary statistics offer concise insights into data, facilitating comparisons and simplifying analysis[105]. However, they can be subjective, relying on expert experience, and may distort information [106]. Additionally, due to the multiple independent variables present in hand function assessment [85], it is important to consider statistical methods to be capable of analyzing the multi-factor model, such as multiple linear regression [107].

ML methods have been increasingly used in various healthcare apps [108]. In our review, ML methods were mainly used for detecting and classifying patient hand posture, analyzing and classifying behavior patterns (i.e., tremor, bradykinesia, and ROM), and identifying disease severity and prediction. Our review found SVM to be the most commonly used ML algorithm, particularly for disease classification. This may be attributed to the fact that SVM is capable of effectively addressing high-dimensional data with small sample sizes while providing a good generalization performance, and the ability to work with the primary processing stage data [109]. The main limitation of the SVM algorithm is its inability to handle multi-class classification problems without additional modifications or extensions [110].

Strengths and limitations of the study

The strengths of this review are: 1) the relevant database searches were conducted in a

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comprehensive and reproducible way; 2) this is the first review that aims to comprehensively discuss the role of smartphones and their functionalities in hand assessment from a holistic perspective; 3) this study provides an analytical demonstration of the technical feasibility and advantages of utilizing smartphones for hand function assessment across various domains, including sensor support, clinical practice, and application scenarios. It offers specific guidance on potential future technological directions for application, such as multi-sensor fusion, gold standard establishment, real-time assessment, and machine learning algorithms for data analysis exploration. The review also has some limitations: 1) Given that smartphone-based hand function assessment is in its nascent field, the relevant literature number is limited and source. These may contribute to a lack of sufficient evidence, completeness, and comprehensiveness in research materials, posing challenges in supporting viewpoints, drawing conclusions, and gaining a comprehensive understanding of the field. In addition, this review only encompasses studies with the English language; 2) Due to the exploratory and development nature of this topic, the literature quality varied, with potential limitations such as inconsistency and lack of high-quality reference studies, as well as meta-analysis.

Conclusion and future research

This systematic review focused on how smartphones are used for hand function assessment. It covers evaluating and measuring hand dysfunction results from various diseases, different embedded smartphone sensors, and statistical and AI methods for hand function assessment. Evidence demonstrated that smartphones could provide a convenient, inexpensive, and reliable hand-functional assessment [9, 46, 111]. Future research could (1) explore how to develop a set of the gold standard for smartphone-based hand function assessment; (2) take advantage of smartphones' integrated systems with multiple sensors to collect patients' data in various dimensions to assess hand function holistically; (3) develop ML methods that are more suitable for processing data collected by smartphones. Based on smartphone growing capabilities in data collection and analysis, it is promising that digital technology will bring revolutionary changes in hand function assessment.

Acknowledgments

This work was performed with close collaboration among researchers affiliated with the University of Toronto and Huazhong University of Science and Technology Collaborative Center for Robotics and Eldercare. The authors also thank the rehabilitation professionals at the Hubei Provincial Hospital of Traditional Chinese Medicine.

Funding Statement

This study was supported by the National Natural Science Foundation of China (71771098).

Data Availability

The primary data for this study include the data extraction materials and quality assessments of the included papers, which are presented in the manuscript tables. Additional supporting data related to this review can be obtained from the authors upon request.

Authors' Contributions

All authors were involved in conception and design of the study, methodology, and approved the protocol. JB was responsible for overseeing the search of databases and literature. YZ and YF handled the management of database and deduplication or records. YZ, YF and BY were involved in the screening of citations and data extraction. YZ was responsible for the software, formal analysis, investigation, writing – original draft and review and editing, and visualization. YF and BY were responsible for the writing – original draft, supervision, and project administration. YZ, KG, and AM are responsible for the conceptualization and the wirting-review and editing.All authors supported in revising and formatting of the manuscript. All authors have provided final approval of the version of the manuscript submitted for publication, and all authors agree to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

AFT: Alternating finger-tapping.
APP: Application.
BagDT: The bagged ensemble of the decision tree.
CAPSIT-PD: The Core Assessment Program for Surgical Interventional Therapies in Parkinson's Disease.
CIT: Cognitive Interference Test.
CMCj: Carpometacarpal joint.
CNN: Convolutional neural networks.
CTS: Carpal tunnel syndrome.
DIPj: Distal interphalangeal joint.
DNM: Did not mention.
DNN: Deep Neural Network.
DT: Decision tree.
EMD: Empirical mode decomposition.
ET: Essential tremor.
FSR: Force sensing resistor.
FT: Functional tremor.

HAR: Human Activity Recognition.
HC: Health control.
HD: Huntington’s disease.
IMU: Inertial measurement unit.
k-NN: kth nearest neighbor algorithm.
LTB: Long-term behavior.
Magα: The sums of squared magnitudes of the acceleration.
Magω: The sums of squared magnitudes of the rotation rate vector.
mAmpω: The maximum sums of the three axial components of the rotation vector ω calculated by Fourier transform.
MBRS: Modified Bradykinesia Rating Scale.
MCPj: Metacarpophalangeal joint.
MDS-UPDRS: Movement Disorder Society of Unified Parkinson's Disease Rating Scale.
MFCC2: Mel-frequency cepstral coefficient2.
MS: Multiple sclerosis.
N/A: Not applicable.
NB: Naive Bayes.
Neuro-QoL: Quality of Life in Neurological Disorders.
PD: Parkinson's disease.
PDDN: These patients’ UPDRS scores are the ones evaluated while the patients were on medication.
PDDS: Patient-Determined Disease Steps.
PDQ-8: 8-question Parkinson’s Disease Questionnaire.
PIPj: Proximal interphalangeal joint.
RA: Rheumatoid arthritis.
RAM: Rapid Alternating Movements.
RBF: Radial basis function.
RF: Random forest.
RMS: Root means square.
ROM: Range of motion.
SD: Standard deviation.
Sdα: The sums of absolute differences in the acceleration vector.
SMA: Simple moving average.
SmT: Smartphone tapper.
STB: Short-term behavior.
SVM: Support vector machine.
TTT: Time tapping test.
UHDRS: Unified Huntington Disease Rating Scale.
YHC: Young health control.

Supplementary Files

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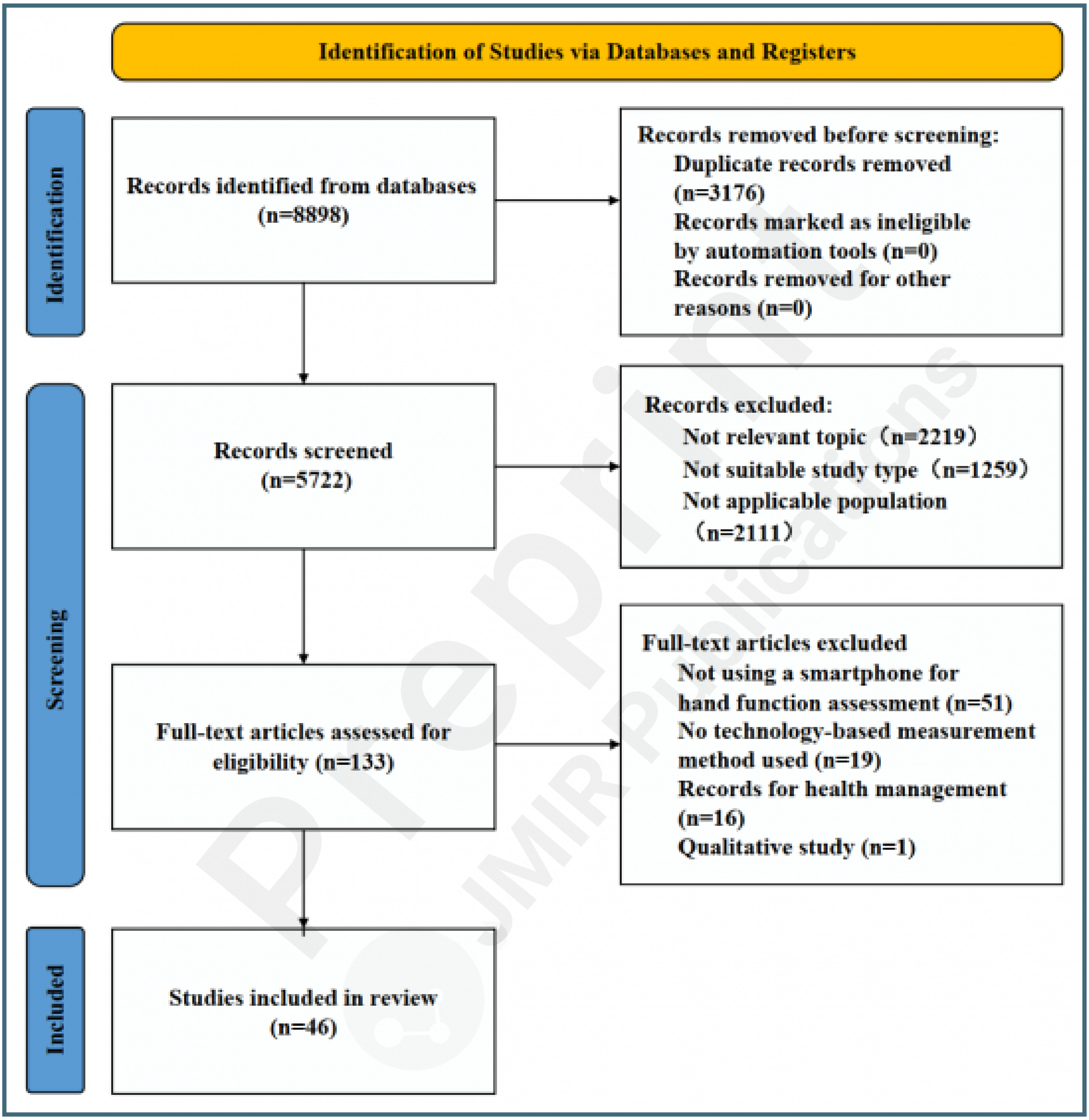
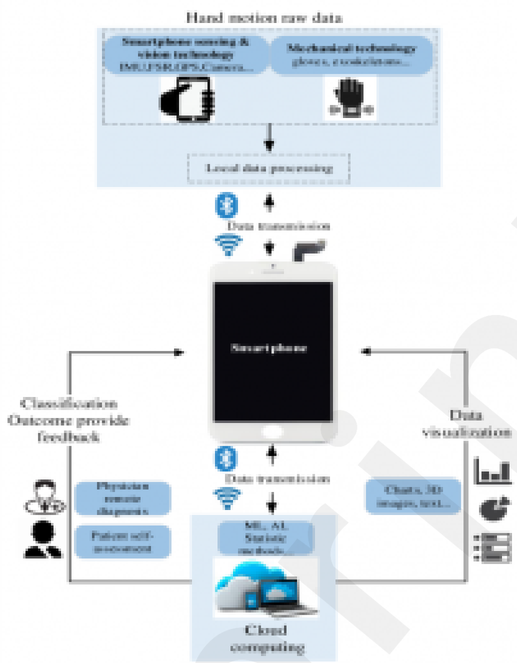
Figures

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram illustrating the screening process for papers included in this study.



The primary design ideas for the development of smartphone-based hand function assessment technology.



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Multimedia Appendixes

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
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