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MAYO CLINIC PROCEEDINGS: DIGITAL HEALTH

REVIEW

In Situ Physiologic and Behavioral Monitoring With Digital Sensors for Cerebrovascular Disease: A Scoping Review

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Abstract

Cerebrovascular disease (CeVD) is a leading cause of death and disability worldwide. Early detection of behavioral and physiologic changes associated with CeVD may be critical to improving patient outcomes. The growing prevalence of remote monitoring tools, from wearable devices to smartphone applications, which facilitate *in situ* observation of patients, holds promise for more timely recognition and possible prevention of stroke. The goal of this review was to examine and establish categories of innovation with digital sensors that monitor physiologic and behavioral variables *in situ* to augment the current CeVD screening and diagnostic processes. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses checklist, a search strategy spanning multiple databases from January 2012 to September 30, 2022, was implemented, aggregating 729 articles, of which 51 (7.0%) met the inclusion criteria. The articles were divided into 2 categories on the basis of their focus: physiologic and behavioral. Physiologic articles were sorted into 1 of the following 6 subcategories according to the signal(s) monitored: motor function, heart rhythm, heart rate, kinematic analysis, physical activity, and blood pressure. Behavioral articles were sorted into the following 3 subcategories: mood, cognitive function, and fatigue. Most studies used a wearable accelerometer, photoplethysmography-enabled smartwatch, or smartphone-based sensors. This scoping review identified disparate methods and conclusions associated with the use of digital sensors for *in situ* physiologic and behavioral monitoring of patients with CeVD. Although most articles evaluated pilot validation and feasibility trials, the lack of randomized controlled trials was identified as a critical gap specific to this evolving research area.

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Identifying patterns of behavioral and physiologic signals that occur before or at the time of an adverse event may be the key to delivering timelier interventions that prevent death and disability.[1] The capability to monitor and detect abnormal patterns in these signals has been accelerated by the widespread adoption of wearable devices and smartphones with digital sensors. From commercially available fitness devices, such as Fitbit, to modern smartphones, numerous everyday devices contain built-in digital sensors capable of collecting active data, such as electrocardiogram (ECG) readings and patient-generated survey responses, and passive data, such as an accelerometer and global positioning system values. In contrast to the temporarily limited data used by clinicians, such as laboratory tests and self-reported symptoms, remote monitoring *in situ* has the potential to augment clinician decision-making by providing information about patients and their daily environments outside clinical settings.[2] Digital sensor data can provide context regarding the variability of physiologic and behavioral signals and can facilitate real-time monitoring of patient symptoms outside of clinical environments before they exceed thresholds indicative of a medical emergency. Moreover, the aggregation of pertinent continuous data could capture physiologic and behavioral signal anomalies that inform the discovery of

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previously unknown disease-related phenotypes.[3] Although *in situ* behavioral and physiologic monitoring is a growing research area, little is known about its application for patients with or at risk of cerebrovascular disease (CeVD).

With a shortage of clinical experts relative to the incidence of CeVD worldwide, remote observation of relevant symptoms is hypothesized to potentially augment the current screening and monitoring practices for CeVD.[4] To detect symptoms indicative of CeVD, clinicians routinely monitor patient heart rhythm, heart rate, and blood pressure.[5,6] Detecting abnormal heart conditions, such as atrial fibrillation (Afib), is critical to delivering preventive care for patients at risk of ischemic stroke (IS), a type of CeVD.[7] In contrast to patients at risk of IS, those at risk of hemorrhagic stroke (HS) are more likely to experience acute headache, eye impairment, and more profound motor impairment, including seizures, before stroke onset.[8] After a CeVD diagnosis, clinicians frequently assess short-term and long-term outcomes by evaluating motor function, kinematic analysis, and physical activity, as well as fatigue, mood, and cognitive function.[9] Transient ischemic attack (TIA), another type of CeVD, is a stroke precursor event characterized by short-term symptoms of unilateral weakness or speech impairment and linked to high blood pressure.[10] Patients with amaurosis fugax related to transient central retinal artery occlusion (CRAO) or branch retinal artery occlusion, types of CeVD identifiable by characteristic vision loss patterns, are also at an increased risk of stroke and TIA.[11] Subarachnoid hemorrhage, a type of CeVD and a risk factor for stroke characterized by bleeding into the space surrounding the brain, often presents with suddenly decreased consciousness and acute headache.[12] Over time, CeVD events can contribute to vascular or multi-infarct dementia, a CeVD condition marked by changes in cognition and mood.[13] Thus, multiple cerebrovascular disease conditions can present as symptoms identifiable before a life-threatening CeVD event, such as a stroke, or CeVD-linked disability becomes permanent.

Complicating the identification of physiologic or behavioral abnormalities is the fact that indeterminate diagnosis and misdiagnosis are frequent for CeVD. Subarachnoid hemorrhage, which is linked to HS, has a misdiagnosis rate of up to 51%.[14] The diagnosis of CRAO is sometimes missed owing to a lack of physician training in relevant techniques.[15] As TIA shares symptoms with numerous conditions, the exact incidence of TIA is unknown.[16] Moreover, for strokes with no identifiable origin after diagnostic workup, the term cryptogenic stroke (CS) is applied to up to 30% of all ISs.[17] Consequently, the potential of new tools such as digital sensors to enhance current understanding of physiologic and behavioral abnormalities before a life-changing CeVD event holds promise for mitigating diagnostic challenges.

ARTICLE HIGHLIGHTS

- Although wearable and smartphone digital sensors can augment in-person and facilitate remote diagnoses of cerebrovascular disease (CeVD), they require a careful review by clinicians.
- Monitoring and detecting a range of abnormal physiologic and behavioral signals, modern digital sensors may be able to predict stroke occurrence and timing.
- When implemented for *in situ* patient monitoring, digital sensors have the potential to enhance screening, detection, or severity grading for CeVD-related clinical sequelae, such as cognitive impairment, depression, gait changes, or falls.
- With limited information about patient CeVD diagnoses or multiple CeVD conditions evaluated as a category in most studies, no conclusion can be drawn regarding optimal participant demographic characteristics or sampling time points using digital sensors in CeVD research.

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The ability to track and review data correlated with relevant variables and symptoms using digital sensors outside of clinical settings has the potential to augment clinical decision-making for CeVD in the coming years. We aimed to assess the landscape of studies that used wearable or smartphone-based digital sensors to aggregate continuous data of patients at risk of or diagnosed with different CeVD conditions outside of clinical settings.

METHODS

This scoping review examined studies that used wearable and/or smartphone-based digital sensors for passive and active monitoring of patients at risk of or diagnosed with CeVD (Figure 1). For this review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines were used (Figure 2).

Step 1: Formulating a Research Question

We conducted a search strategy to review the current literature with the following objectives: (1) to understand how digital sensors are being applied to CeVD monitoring by identifying the sensors used, the physiologic and behavioral signals they monitor, and the CeVD conditions monitored and (2) to evaluate how the use of digital sensors outside of clinical settings has augmented knowledge of CeVD. For this review on *in situ* monitoring, a digital sensor was broadly defined as any sensor built into a wearable device or smartphone (or mobile tablet similar in size and operating system).

Step 2: Executing a Search Strategy

A search strategy using controlled vocabulary terms with relevant keywords (Supplemental Appendix 1, available online at https://www.mcpdigitalhealth.org/) was designed by study investigators (S.J.Z., B.J.E., and B.M.D.). The search was performed using multiple databases on September 30, 2022, limited to articles published between January 2012 and September 2022. The databases queried were Scopus (hosted by Elsevier [≥1788]); Web of Science core collection (hosted by Clarivate Analytics [≥1975]); Ovid Cochrane Central Register of Controlled Trials (≥1991); Ovid Embase (≥1988); and Ovid MEDLINE (≥1946), in addition to Epub ahead of print, in-process, and other nonindexed citations and daily (identical to PubMed).

Conditions and tools used to develop the search strategy, combined using "AND"

Search conditions, combined using "OR"

- Cerebrovascular disease
- Cerebrovascular diseases
- Stroke
- Ischemic stroke
- Hemorrhagic stroke
- Transient ischemic attack
- TIA
- Subarachnoid hemorrhage
- SAH
- Central retinal artery occlusion
- CRAO
- Vascular dementia
- Multi-infarct dementia

Search tools, combined using "OR"

- Smart watch
- Smartwatch
- Apple watch
- Smart glasses
- Google glass
- Smartphone
- Smartphone app
- Smartphone intervention
- Fitness tracker
- Activity tracker
- mHealth
- Mobile app

FIGURE 1. Conditions and tools used to develop the search strategy. app, application; CRAO, central retinal artery occlusion; SAH, subarachnoid hemorrhage; TIA, transient ischemic attack.

Step 3: Selecting Studies

This process consisted of 2 steps: first, title and abstract screening, and, second, a full-text review. In the first step, 2 investigators (S.J.Z. and N.H.A.) screened articles and excluded the following types: review articles, studies not focusing on patients at risk of or diagnosed with CeVD, protocols, editorials/comments/other similar articles, abstracts or presentations, studies not available in English, and exclusively qualitative studies (Table 1). The final list of studies for the first step was reviewed by 2 other investigators (B.M.D. and B.J.E.).

In the second step, a full-text review was executed by 2 investigators (S.J.Z. and N.H.A.) to create the final source list. The following were excluded: studies focused on

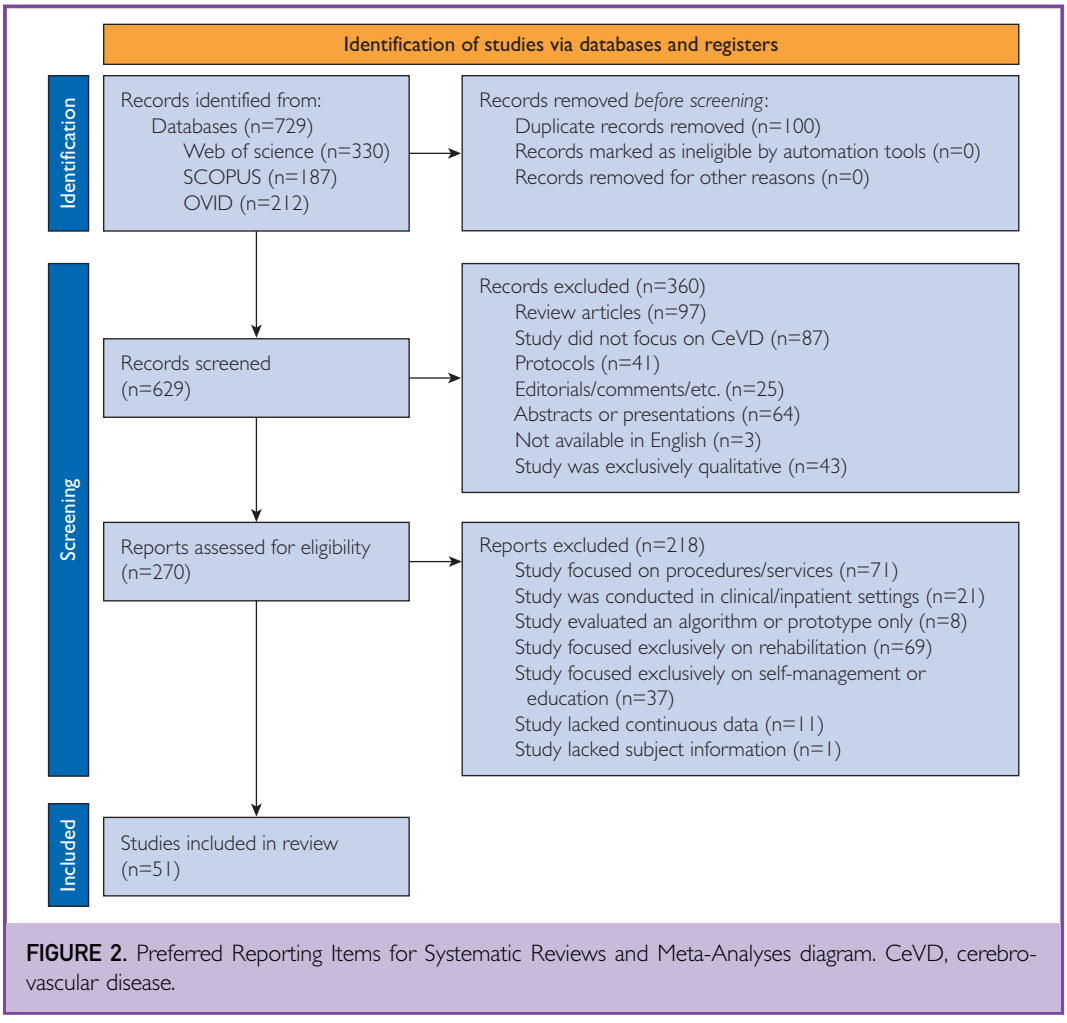

FIGURE 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses diagram. CeVD, cerebrovascular disease.

procedures or clinical services, studies conducted in an inpatient or clinical setting (without simulating real world conditions), prototype design studies, algorithm validation studies, studies focused exclusively on self-management or education, studies lacking continuous data (defined as collecting measurements at least once per day), and studies lacking sample population information. For both physiologic and behavioral signal collection, studies focused exclusively on rehabilitation for patients with CeVD, without consideration for the generalizability of results beyond rehabilitation programs or settings, were excluded (Table 1).

Step 4: Analyzing Data

Data from studies on the final source list were primarily extracted by 1 investigator (S.J.Z.): authors, year, study design, sample characteristics, baseline participant diagnosis, smartphone application or wearable device, measured signals, data collection interval, and key limitations. A second investigator (N.H.A.) extracted data for the application/device column (Table 2).[18–68] Studies were grouped by monitoring focus (physiologic or behavioral) and categorized according to the signal type monitored (mood, cognitive function, fatigue, motor function, heart rhythm, heart rate, kinematic analysis, physical activity, and blood pressure).

RESULTS

The initial search found 729 articles. Two study investigators (S.J.Z., N.H.A.) screened the titles and abstracts of the articles to pare the source list and remove duplicate articles.

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TABLE 1. Rationale and Eligibility Criteria for Inclusion and Exclusion

Eligibility criteria and variable	Rationale
Inclusion criteria	
Real-world (*in situ*) setting	Data must be collected from studies conducted outside of clinical environments or in an environment simulating real-world conditions
Participants potentially at risk of primary or secondary CeVD diagnosis	Study must be focused on participants who have either been previously diagnosed with CeVD, such as stroke, or who are potentially at risk of CeVD
Peer-reviewed manuscript	Owing to the review of experts, studies had increased credibility
Tool facilitating continuous monitoring (defined as a minimum data collection interval of once daily)	Tool studied must collect frequent data from participants to facilitate remote monitoring
Empirical study	Study design must outline hypotheses and research questions rather than present opinions
Published between January 2012 and September 2022	Focused on studies conducted in the past decade owing to rapid adoption of digital tools and software in recent years
Available in English	Constraint filter applied owing to language proficiency of investigators
Sample population information included	At minimum, the number of study participants must be published
Exclusion criteria	
Nonempirical studies	To reduce bias associated with personal or organizational viewpoints, nonempirical studies, such as editorials, commentaries, society statements, and opinion pieces, were excluded. Review articles, abstracts, presentations, and protocols were excluded
Exclusively qualitative studies	Given the limited number of large-scale study results published in the remote monitoring space, studies exclusively qualitative in scope were excluded to reduce the likelihood of bias resulting from small sample size, nonrepresentative sample population demographic characteristics, or geographic location
Studies not focused on risk factors for CeVD	Because this review explored remote monitoring of behavioral and physiologic variables relevant to CeVD, studies not considering risk factors for CeVD were excluded
Studies focused on clinical services, procedures, or rehabilitation	Studies conducted in clinical settings or exclusively focused on preprocedural or postprocedural outcomes were excluded
Studies focused exclusively on self-management or education	Because this review explored remote monitoring, studies on tools assisting patients with self-management or education were excluded
Prototype design and algorithm validation studies	Given that the review aimed to characterize the current state of *in situ* remote monitoring for CeVD, studies on tools that were evaluated with participants or that focused exclusively on algorithm design and testing were not appropriate for this review

CeVD, cerebrovascular disease.

Two other investigators reviewed the source list and reconciled disagreements related to inclusion criteria (B.J.E. and B.M.D.). At this point, 63.1% (460/729) of the articles were excluded from the source list because they did not meet the inclusion criteria. Then, a full-text screening of the 37.0% (270/729) of the included articles was conducted by 2 study

TABLE 2. Summary of Studies on the Use of Digital Sensors in *In Situ* Monitoring for Cerebrovascular Disease

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Physiologic monitoring							
Beerten et al,[18] 2021	Prospective longitudinal cohort study in RWS	92 Ps; 56 M, 36 F; race, NR	Previous TIA/UTS (10); at risk of Afib (92)	FibriCheck PPG application (Quompium)	Heart rate (smartphone camera sensor)	2 Ms/d for 14 d	TIA and UTS patients not studied separately; unknown date of TIA/UTS
Bensalah et al,[19] 2021	Pilot study in-laboratory —simulated RWS	29 Ps; 16 M, 13 F; race, NR	Healthy (25); previous UTS (4)	Apple watch 4 (Apple)	Motor function (accelerometer, gyroscope, magnetometer, and altimeter)	Continuous for 1 session	UTS; unknown date of stroke
Bochniewicz et al,[20] 2017	Pilot study in simulated RWS	20 Ps; 12 M, 8 F; race, NR	Healthy (10); previous UTS >6 mo before (10)	ADIS16400BMLZ inertial measurement unit (Analog Devices)	Motor function (accelerometer)	Continuous for 1 session	UTS
Capela et al,[21] 2016	Pilot study in simulated RWS	30 Ps; sex and race, NR	Healthy (15); previous stroke (13 IS; 1 SAH; 1 cerebral tumor) occurred 9.6 mo before (avg)	BlackBerry Z10 smartphone (BlackBerry)	Motor function (accelerometer and gyroscope)	Continuous for 1 session	IS and SAH not studied separately
Chang et al,[22] 2022	Feasibility study in RWS	200 Ps; 127 M, 73 F; race, NR	Afib (112); at risk of Afib (88)	Garmin Forerunner 945 smartwatch (Garmin)	Heart rate (smartwatch PPG sensor)	Continuous for 24 h	Only 7.7±3.1 h of PPG signals studied
Chen et al,[23] 2021	Pilot study in simulated RWE	11 Ps; 8 M, 3 F; 6 Caucasians, 4 AAs, and 1 unknown	Previous UTS more than 6 mo before (11)	Apple Watch Series 3 (Apple)	Motor function (accelerometer and gyroscope)	Continuous for 1 session (3 h) during 2 visits	UTS
Choi et al,[24] 2015	Pilot study in simulated RWS	60 Ps; 47 M, 13 F; race, NR	Poststroke with aphasia (21 ISs; 9 HSs); poststroke without aphasia (20 ISs; 10 HSs)	iPad MAST application (Apple)	Motor function (smartphone-based speaker sensor)	Continuous for 1 session	IS and HS not studied separately; unknown date of stroke

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Costa et al,[25] 2020	Pilot study in laboratory	55 Ps; 30 M, 25 F; race, NR	Previous stroke >6 mo prior (44 ISs; 11 HSs)	With smartwatch: Google Fit application (Google), STEPZ application (Appsthat.rocks), Pacer application (Pacer); Without smartwatch: Fitbit Ultra waist-clip pedometer (Fitbit)	Physical activity (accelerometer and gyroscope)	Continuous for 2-min walk test	IS and HS not studied separately
Dutta et al,[26] 2020	Proof-of-concept study in laboratory	2 Ps; 2 M; race, NR	Healthy (1); previous UTS >6 mo prior (1)	Prototype smart glove	Motor function (bend sensors, pressure sensors, and accelerometers)	Continuous for 1 session	UTS
Feld et al,[27] 2018	Pilot study in RWS	28 Ps; 17 M and 11 F; race, NR	Previous stroke within past 3 y (20 ISs; 8 UTS)	LEGSys (Biosensics)	Kinematic analysis (inertial sensors)	Continuous for 48 h	UTS for 8 participants
Feldman et al,[28] 2022	Retrospective observational cohort study in RWS	1802 Ps; 1154 M, 648 F; 1223 Whites, 179 Asians, 153 Blacks or AAs, 138 other, 109 unknown; 239 Hispanics	Unspecified (1802)	Apple watch (Apple)	Heart rate (smartwatch PPG sensor)	Continuous with minimum wear of 60 min/d	Study only estimates anticoagulation benefit of detecting Afib
Fonte et al,[29] 2022	Pilot study in laboratory	30 Ps; 17 M, 13 F; race, NR	Hemiparetic after previous stroke within past 6.6 y (12 ISs; 18 HSs)	wGT3X-BT (ActiGraph)	Physical activity (accelerometer)	Continuous for 1 session	IS and HS not studied separately
Godkin et al,[30] 2021	Pilot study in RWS	39 Ps; 25 M, 14 F; race, NR	CeVD (10); neurodegenerative disease (29)	GENEActiv Originals (ActivInsights); Bittium Faros 180 (Bittium)	Motor function (accelerometer, temperature sensor, light sensor, and ECG)	Variable	CeVD types unspecified; unknown date of CeVD diagnosis

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Guo et al,[31] 2019	Large population-based cohort study in RWS	187,912 Ps; 162,920 M, 24,992 F; race, NR	Unspecified (187,912)	Honor Band 4 wristband or Huawei Watch GT or Honor Watch (Huawei Technologies)	Heart rate (smartwatch PPG sensor)	Continuous with minimum wear of 14 d	38% of participants were lost to follow-up
Ha et al,[32] 2021	Randomized clinical trial in RWS	336 Ps; 263 M, 73 F; 133 Whites, 19 Asians, 4 Blacks, 1 First Nations, 3 Hispanics/ Latinos, 3 other	Postcardiac operation patients at risk of stroke (336); previous TIA/UTS (35)	ECG wearable patch (Medtronic SEEQ System or Incentia CardioSTAT System)	Heart rhythm (wearable ECG patch)	Continuous for 30 d	Patients with TIA/ UTS not studied separately; unknown date of TIA/UTS
Honado et al,[33] 2022	Feasibility study in RWS	120 Ps; sex and race, NR	Healthy (60); UTS (60)	Garmin Forerunner 15 (Garmin)	Physical activity (pedometer)	Continuous for 7 d	UTS; unknown date of UTS
Hughes et al,[34] 2019	Pilot study in laboratory	14 Ps; 13 M, 1 F; race, NR	Acquired brain injury within past 5 y (2 TBIs; 8 ISs; 2 HSs; 1 TIA)	Prototype outREACH wearable wristwatch	Motor function (accelerometer, gyroscope)	Continuous for 1 session	Patients with TIA, IS, HS not studied separately
Hui et al,[35] 2018	Pilot study in RWS	12 Ps; 7 M, 5 F; race, NR	Previous UTS within past 9 y (12)	Fitbit One (FitBit); Actical accelerometer (Philips)	Physical activity (accelerometer)	Continuous for 3 d	UTS
Ichwana et al,[36] 2018	Proof-of-concept study in laboratory	3 Ps; sex and race, NR	Patient with simulated TIA (3)	Prototype wearable waist device with accelerometer, gyroscope, and GPS sensor	Motor function (accelerometer, gyroscope, and GPS sensor)	Continuous for 1 session	Patients with simulated TIA without a real diagnosis
Koh et al,[37] 2021	Randomized controlled trial in RWS	203 Ps; 152 M, 51 F; race, NR	Previous IS/TIA within past 12 mo (203)	KardiaMobile (AliveCor)	Heart rhythm (smartphone-linked ECG)	Continuous for 30 d	TIA and IS not studied separately
Kovoor et al,[38] 2021	Case report in RWS	1 P; 1 M; race, NR	Previous paroxysmal Afib (1)	Unspecified smartwatch	Heart rate (unspecified)	Unspecified	Case report; unknown date of paroxysmal Afib diagnosis

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Lakshminarayanan et al,[39] 2018	Randomized controlled trial in RWS	50 Ps; 36 M, 14 F; 45 Whites	Previous UTS (50)	Withings wireless BP monitor (Nokia)	Blood pressure	1 Ms/d for 3 mo	UTS; unknown date of UTS
Lang et al,[40] 2021	Prospective longitudinal cohort study in RWS	67 Ps; 37 M, 30 F; 39 Caucasians, 27 Blacks or AAs, 1 Asian or Pacific Islander; 67 Non-Hispanics	Upper-limb paresis after stroke within 14 d before (59 ISs; 8 HSs)	Actigraph Link Accelerometer (Actigraph)	Motor function (accelerometer)	Continuous for 24 h at time points 2, 4, 6, 8, 12, 16, 20, and 24 wk	IS and HS not studied separately
Lee et al,[41] 2021	Secondary analysis of clinical trial data in RWS	128 Ps; 98 M, 30 F; 122 Whites; 108 Non-Hispanics	Afib (90); at risk of Afib (38); previous TIA/UTS (88)	KardiaMobile (AliveCor)	Heart rhythm (smartphone-linked ECG)	2 Ms/d for 6 mo	Patients with TIA/UTS not studied separately; unknown date of TIA/UTS
Li et al,[42] 2020	Cross-sectional study in simulated RWS	314 Ps; 144 M, 170 F; race, NR	Cerebral small-vessel disease (314)	Sennogait (Sennotech)	Kinematic analysis (stride time, cadence, stance phase time percentage, maximum swing velocity, stride length, heel-strike angle, toe-off angle)	Continuous for 1 session	Unknown date of CSVD diagnosis
Ma et al,[43] 2022	Pilot study in simulated RWS	68 Ps; 35 M, 33 F; race, NR	Cerebral small-vessel disease (46); healthy (22)	IDEEA	Kinematic analysis (stride time, stride length, speed, cadence, swing time)	Continuous for 1 session	Unknown date of CSVD diagnosis
Noorian et al,[44] 2019	Pilot study in RWS	17 Ps; 12 M, 5 F; race, NR	Suspected UTS (17)	Google Glass (Google)	Motor function (camera and speaker sensors)	Continuous for 1 session	UTS
Pagola et al,[45] 2022	Prospective observational cohort study in RWS	163 Ps; 102 M, 61 F; race, NR	CS occurring 24 h prior (163)	Wearable fabric-based Holter monitor (Nuubo)	Heart rhythm (wearable ECG monitor)	Continuous for 90 d	27% of participants withdrew

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Park et al,[46] 2019	Feasibility study in simulated RWS	276 Ps; sex and race, NR	Previous UTS (68); healthy (208)	Dynafoot2 Insole sensor (Dynafoot)	Kinematic analysis (accelerometer. insole pressure sensor, pedometer, GPS, and footswitches)	Continuous for 1 session	UTS; unknown date of UTS
Patel et al,[47] 2021	Case report in RWS	1 P; 1 F; race, NR	Previous embolic (ischemic) CS (1)	Apple watch (Apple)	Heart rate (smartwatch PPG sensor)	Unspecified	Case report
Perez et al,[48] 2019	Single-arm clinical trial in RWS	419,297 Ps; 238,700 M, 177,087 F, 396 other, 3114 NR; 286,190 Whites, 48,775 Hispanics, 32,275 Blacks, 25,156 Asians, 4696 American Indians, 1493 Pacific Islanders, 3652 Middle Easterns, 7958 other/mixed, 8102 NR	Without Afib (419,297)	Apple watch (Apple)	Heart rate (smartwatch PPG sensor)	Continuous for an average of 117 d	Only 450 of 2161 notified participants communicated with study provider and returned ECG patches
Perino et al,[49] 2021	Secondary analysis of clinical trial data in RWS	450 Ps; 335 M, 102 F, 13 NR; 379 Whites, 20 Hispanics, 16 Blacks, 8 Asians, 3 American Indians, 0 Pacific Islander, 2 Middle Easterns, 6 other/mixed	Without Afib; with an ambulatory ECG patch after index irregular pulse notification	Apple watch (Apple); ECG patch (BioTelemetry)	Heart rate (smartwatch PPG sensor); heart rhythm (wearable ECG patch)	Continuous for 7 d	Only 945 out of 2161 notified participants initiated first study visit

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Phienphanich et al,[50] 2019	Pilot study in laboratory	52 Ps; sex and race, NR	Healthy (32); previous UTS (20)	Prototype smartphone application for FAST-based stroke screening	Motor function (accelerometer, gyroscope)	Continuous for 1 session	UTS; unknown date of UTS
Pickford et al,[51] 2019	Pilot study in RWS	34 Ps; 28 M, 27 F; race, NR	Healthy (22); discharged from hospital with previous UTS within 14 d before (24)	activPAL3 (PAL Technologies)	Motor function (accelerometer)	Continuous for 7 d	UTS
Samal et al,[52] 2020	Case report in RWS	1 P; 1 M; race, NR	Healthy (1)	Apple Watch Series 3 (Apple)	Heart rate (smartwatch PPG sensor)	Continuous passive	Case report
Schaffer et al,[53] 2017	Pilot study in laboratory	24 Ps; 14 M, 10 F; race, NR	Hemiparesis due to stroke occurring >6 mo prior (24)	Fitbit Zip (Fitbit) on the nonparetic hip; Garmin Vivofits (Garmin) on both wrists	Physical activity (pedometer)	Continuous for 6-min walk test	UTS
Simmatis et al,[54] 2022	Pilot study in laboratory and RWS	23 Ps; 15 M, 8 F; race, NR	Within past 7.3 y, previous UTS (23); previous TIA (8)	OPEX (OroPharyngeal EXercise) on Samsung Galaxy Tablet (Samsung)	Kinematic analysis (camera and speaker sensors)	Continuous for laboratory session; continuous for a maximum of 2 sessions/d for 1 mo distributed throughout six 5-d wk	UTS; patients with previous TIA and UTS not separated from patients with previous UTS only
Steinhubl et al,[55] 2018	Randomized clinical trial in RWS	2659 Ps; 1634 M, 1025 F; race, NR	Risk of Afib (2659); previous UTS (369)	Samsung Galaxy Tab A7 tablet (Samsung)	Heart rhythm (wearable ECG patch)	Continuous for up to 4 wk	UTS; unknown date of UTS
Steinhubl et al,[56] 2021	Randomized clinical trial in RWS	5089 Ps; 3016 M, 2073 F; race NR	No diagnosis of Afib (5089); previous UTS (541)	iRhythm Zio^{XT} ECG patch (Zio)	Heart rhythm (wearable ECG patch)	Continuous wear of patch 1 (baseline) followed by patch 2 (at 3 mo for a median total of 24.7 d)	UTS; unknown date of UTS

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TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Tison et al,[57] 2018	Validation study in RWS	183 Ps; incomplete sex and race data	Self-reported arrhythmia; previous UTS (unknown #)	AliveCor (AliveCor) device; Apple watch (Apple)	Heart rhythm (AliveCor Kardia smartphone-based ECG); heart rate (Apple watch smartwatch-based PPG)	1 ECG Ms/d for unspecified time while wearing smartwatch in workout mode	UTS; arrhythmia self-reported; unknown date of UTS; # of participants with previous UTS unknown
Turakhia et al,[58] 2015	Prospective observational cohort study in RWS	75 Ps; 75 M; 67 Whites, 8 Non-whites	At risk of Afib or UTS (75)	Wearable ECG patch (iRhythm Technologies)	Heart rhythm (wearable ECG patch)	Continuous for 14 d	Only M participants
Vera et al,[59] 2021	Pilot study in RWS	63 Ps; 28 M, 35 F; race, NR	With recent IS or TIA of unknown etiology (63)	Wearable fabric-based Holter monitor (Nuubo)	Heart rhythm (wearable ECG monitor)	Continuous for 15 d	Patients with TIA/IS not studied separately
Wang et al,[60] 2021	Retrospective propensity-matched cohort study in RWS	16,320 Ps; 9450 M, 6870 F; 14,542 Whites	1 Afib-specific event (ICD-10 code) from 2017 through 2019 (16,320)	Various	Heart rate (smartwatch PPG sensor)	Continuous for 90 d	Single-center study
Weichert,[61] 2019	Case report in RWS	1 P; 1 F; race, NR	TIA 2 mo prior (1)	Apple watch Series 2 (Apple)	Heart rate (smartwatch PPG sensor)	Continuous	Case report
Wouters et al,[62] 2022	Case report in RWS	1 P; 1 M; race, NR	Current CS (1)	FibriCheck application on smartphone	Heart rate (smartphone camera sensor)	2 Ms/d for 6 mo	Case report
Wouters et al,[63] 2022	Preliminary results from a clinical trial in RWS	39 Ps; 27 M, 12 F; race, NR	Patients with previous cyptogenic stroke (24) or TIA (15) with an ICM	FibriCheck application on smartphone vs smartwatch	Heart rate (smartwatch PPG sensor) vs heart rate (smartphone camera sensor)	2 Ms/d for 6 mo	Preliminary results; CS and TIA not studied separately unknown date of stroke/TIA
Zhang et al,[64] 2019	Pilot study in RWS	361 Ps; 171 M, 190 F; race, NR	Without pacemaker or implanted defibrillator (361); previous UTS/TIA (4)	Honor Band 4 wristband or Huawei Watch GT or Honor Watch (Huawei Technologies)	Heart rate (smartwatch PPG sensor)	Continuous for 14 d	UTS and TIA not studied separately; unknown date of UTS/TIA

Continued on next page

TABLE 2. Continued

Reference, year	Study design	Sample characteristics	Baseline participant diagnosis	Smartphone application or wearable device	Measured signals	Data collection interval	Key limitations
Behavioral monitoring							
Forster et al,[65] 2022	Pilot study in inpatient setting	20 Ps; 6 M, 14 F; race, NR	Previous ischemic or hemorrhagic infarct (unknown #)	Android movisensXS application (movisensXS)	Mood and self-evaluation (smartphone surveys)	8 surveys/d for 7 d	Infarct types not studied separately; unknown date of CeVD diagnosis
Forster et al,[66] 2020	Pilot study in inpatient setting	15 Ps; 11 M, 4 F; race, NR	Acquired brain injury within 2.2 y prior (8 cerebral infarction; 3 traumatic brain injury; 1 encephalitis; 1 HS; 2 ruptured brain aneurysms)	Android movisensXS application (movisensXS)	Mood and self-evaluation (smartphone surveys)	8 surveys/d for 7 d	CeVD types not studied separately
Jung et al,[67] 2019	Pilot study in inpatient setting	12 Ps; 1 M, 11 F; race, NR	Mild cognitive impairment with previous stroke within 13 y before (11 ISs; 1 HS)	Prototype Neuro-World on Tablet Galaxy Note Pro (Samsung)	Cognitive impairment level (game performance)	Continuous for 30 min/d, twice per week, for 3 mo	CeVD types not studied separately
Lenaert et al,[68] 2022	Pilot study in outpatient setting	26 Ps; 14 M, 12 F; race, NR	Previous UTS	PsyMate smartphone application (Maastricht University)	Fatigue (smartphone surveys)	10 surveys/d for 6 d	UTS; unknown date of CeVD diagnosis

AA, African American; Afib, atrial fibrillation; avg, average; BP, blood pressure; CeVD, cerebrovascular disease; CS, cryptogenic stroke; CSVD, cerebral small-vessel disease; ECG, electrocardiogram; F, female; FAST, Face, Arm, Speech, and Time; GPS, global positioning system; HS, hemorrhagic stroke; ICD-10, International Classification of Diseases, 10th Revision; ICM, insertable cardiac monitor; IDEEA, Intelligent Device for Energy Expenditure and Activity; IS, ischemic stroke; M, male; Ms, measurement; NR, not reported; P, participant; PPG, photoplethysmogram; RWS, real-world setting; SAH, subarachnoid hemorrhage; TIA, transient ischemic attack; TBI, traumatic brain injury; UTS, unspecified type of stroke.

investigators (S.J.Z. and N.H.A.). The final source list included 51 of the initial 729 articles (7.0%) and was evaluated by all the investigators.

The final source list (Table 2) consisted of studies published between 2015 and 2022 conducted in Europe, Asia, and the United States. The synopses of included studies are grouped further according to monitoring focus and by signal type monitored.

Physiologic Monitoring

Most studies (47/51, 92.2%) applied digital sensors to monitor physiologic signals in patients diagnosed with or at risk of CeVD.

Motor Function. Approximately one-fourth of the included studies (13/51, 25.5%) focused on using digital sensors to measure motor function in patients with CeVD.

A pilot study by Bensalah et al[19] used data recorded from 29 healthy participants and poststroke participants who completed sequences of specific movements while wearing an Apple watch 4 on both wrists to consider the fact that patients with stroke tend to experience pronounced motor defects in one side of the body. Data from multiple smartwatch sensors were processed and segmented according to specific movements using 2 approaches—measuring the entire movement or only a gesture associated with it—by machine learning classification methods. The results found that the support vector machine model approach using data recorded from the action segmentation data generated the most accurate classification (84%); however, for real-time monitoring of motor function using smartwatches, the results suggest that, regardless of the classification approach, a gesture-only sampling method is optimal. Bochniewicz et al[20] measured a functional arm movement in 10 chronic poststroke patients and 10 healthy participants with an Analog Devices wristwatch accelerometer. While performing a series of structured movements, the participants wore the wristwatch and were simultaneously videotaped. After processing the wristwatch data, a random forest machine learning model was used to classify data according to structured movements. Comparing the video recordings to wristwatch data annotation, the correct classification of movements for poststroke patients was 88.38%.

One pilot study quantified wearable accelerometer device adherence in patients with CeVD, examining patterns of device removal.[30] They found that adherence with wearing 3 devices simultaneously was exceptionally high overall (median, 98.2%) and higher during daytime hours than at night ($P<.001$). Similarly, Chen et al[23] required 11 chronic poststroke patients to wear Apple watches on both wrists, upper arms, and the hip to record daily living activities. Then, researchers trained machine learning algorithms to classify data recorded during seminatural activities according to the activity type with a high degree of accuracy (>80%). The study by Capela et al[21] also assessed data obtained from the hip region by asking participants to wear a BlackBerry Z10 smartphone on their waist while completing daily living tasks. Accelerometer and gyroscope sensor data recorded during these activities were used to develop a human activity classifier algorithm; however, the accuracy of the algorithm decreased as the task complexity increased for chronic poststroke patients. Pickford et al[51] used the activPAL3 wearable accelerometer, worn on the thighs of 34 healthy participants and recent poststroke patients, to track sit-to-stand and stand-to-sit transitions. Researchers found that the mean peak velocities of both transitions were significantly higher in healthy participants than in poststroke patients (70.7/s±52.2/s vs 44.2/s±28.0/s for sit-to-stand; 74.7/s±51.8/s vs 46.0/s±31.9/s for stand-to-sit).

Using data from 52 healthy participants and poststroke patients, Phienphanich et al[50] evaluated a wearable prototype using a built-in accelerometer and gyroscope. The participants were instructed to curl and raise their arms. Data were processed and classified with an average area under the receiving operating characteristic curve (AUROCC) of 66.2%-81.5% for both movements combined. The accuracy of this prototype and algorithm method was comparable with the standard Face, Arm, Speech, and Time stroke screening approach (accuracy of 69%-77%). Ichwana et al[36] evaluated an internet of things system using a wearable accelerometer to detect movement and falls in patients with TIA.

With 3 participants instructed to perform 9 specified movements, this early-stage system detected 81.48% of falls experienced by the participants. Lang et al[40] also assessed upper-limb (UL) motor function in 67 recent poststroke patients with UL paresis using Actigraph accelerometers worn on both wrists. At specific time points after a stroke (2, 4, 6, 8, 12, 16, 20, and 24 weeks), the participants wore the wristwatches for 24 hours. Researchers found that UL performance stabilized between 3 and 6 weeks after the stroke incidence. Similarly, Hughes et al[34] used a low-cost prototype wristwatch, with built-in accelerometer and gyroscope, to track hand movements in patients with acquired brain injury, including chronic poststroke patients, finding that the wristwatch sensors were sensitive to the levels of impairment as observed by slower and more variable movement for patients with acquired brain injury. A proof-of-concept study by Dutta et al[26] evaluated the potential of a smart glove, with a bend and pressure sensor and accelerometer, to classify upper extremity paresis. Two patients, including 1 chronic poststroke patient, were instructed to perform daily tasks while wearing the glove. The results of the study found an observable deviation between statistical parameters recorded for the poststroke patient and the healthy participant.

Only 2 studies evaluated the use of digital sensors to diagnose patients remotely. One found the feasibility of using Google Glass eyewear camera and speaker sensors to facilitate the visual monitoring and assessment of patients presenting with stroke symptoms by off-site neurologists.[44] Another found an iPad screening tool using speaker sensors to record patient speech for stroke aphasia detection to be comparable with standard aphasia screening tools.[24]

Heart Rhythm. A small percentage of studies (8/51, 15.7%) examined how wearable and smartphone digital sensors could be used to measure heart rhythm in patients *in situ*.

Studying use patterns in patients with Afib assigned to monitoring with the AliveCor ECG for 6 months, Lee et al[41] found that the levels of engagement with monitoring adherence were highly variable and that stroke and TIA survivors were more likely to be moderately engaged with monitoring than other patients with Afib. Pagola et al[45] found that 3-month adherence to wearable Holter monitoring by patients with recent CS was moderately high, with 72.8% of patients completing the protocol. The study investigators also found that patients older than 70 years benefited most from this monitoring protocol. After examining patients with CS, Vera et al[59] enrolled 63 patients with recent stroke of unknown origin in a 15-day wearable Holter monitoring study. Using univariate and multivariate analyses, researchers developed a model to predict Afib in patients with CS and with a higher accuracy than the standard Atrial Fibrilation in Embolic Stroke of Undetermined Source score (0.94 AUROCC vs 0.65 AUROCC; $P<.001$).

In a randomized clinical trial assessing whether screening of asymptomatic individuals for Afib could improve clinical outcomes, a higher rate of Afib diagnosis was reported after 1 year for participants who wore an ECG patch vs those who were not monitored remotely.[55] Patients who were remotely monitored using the ECG patch also had better outcomes, with 6.6% of participants in the nonmonitoring cohort experiencing a stroke and no strokes recorded in the monitoring cohort after 3 years.[56] In this trial, the patients monitored using an immediate ECG facilitated by the wearable patch led to a higher rate of Afib diagnosis compared with patients assigned to a delayed monitoring protocol. In a randomized controlled trial (RCT), in patients aged 55 years and older who had been diagnosed with CS or TIA within the past year, detection of Afib was higher in the 30-day smartphone ECG monitoring (AliveCor KardiaMobile) cohort than the standard 24-hour Holter monitoring group (9.5% vs 2.0%; $P=.024$).[37] Turakhia et al[58] also examined the feasibility of a wearable ECG monitor (iRhythm ECG) in a 2-week prospective screening study with 75 male participants at high risk of Afib. This study detected Afib and sustained atrial tachycardia/Afib in 1 of the 9 and 1 of the 20 participants, respectively. In a similar study, Ha et al[32] assessed whether monitoring of patients at risk of stroke after hospital discharge after cardiac operation could increase Afib detection. Assigning 336 participants to wear an ECG patch, the researchers found that Afib detection increased

by 17.9% within 30 days compared with standard care protocols.

Heart Rate. Most studies (16/51, 31.4%) focused on heart rate monitoring using photoplethysmography (PPG)-enabled smartwatches or smartphone camera–derived PPG readings.

Five studies documented case reports of diagnoses related to heart rate monitoring. Kovoor et al[38] published a case report on 1 male patient previously diagnosed with Afib whose unspecified smartwatch successfully detected premature ventricular complexes and led to a cardiology referral. In a case report of a female patient presenting with an embolic stroke of unknown origin, the patient's Apple Watch PPG readings for 3 weeks after stroke documented multiple episodes of Afib.[47] The smartwatch's readings were of excellent quality, allowing clinicians to diagnose Afib without further investigation. The case report by Samal et al[52] recorded the instance of a young male whose heart palpitations were concurrent with variable heart rate readings recorded by an Apple Watch Series 3, helping clinicians to confirm a diagnosis of Afib. Another case report documented alarms by the Apple Watch Series 2 heart rate monitor as a precursor to Afib diagnosis in a patient with recent TIA.[61] Wouters et al[62] documented a case of a patient with CS whose smartphone PPG application detected a similar rate of Afib episodes compared with an insertable cardiac monitor.

A pilot study in 2021 examined the feasibility of twice daily smartphone PPG monitoring for a minimum of 2 weeks.[18] In a cohort of 86 patients, the smartphone app FibriCheck detected 5 participants with Afib episodes, 2 with tachycardia, and 10 with ectopic beats. Chang et al[22] evaluated the performance of the Garmin Forerunner 945 regarding Afib detection in patients at risk of stroke. With a cohort of 200 participants, each of whom completed simultaneous Holter and smartwatch monitoring for 24 hours, 112 experienced an Afib episode. The smartwatch-based PPG was highly correlated with the gold standard (Holter monitoring), with 97.1% of the Afib segments detected by the Holter examination accurately classified as Afib by the smartwatch. A large cohort study of 187,912 participants using a range of smartwatches to track heart rate found a high degree of accuracy between smartwatch-detected Afib and clinically diagnosed Afib (87.0%) for participants who followed up with a provider.[31] Zhang et al[64] conducted a pilot study with 361 participants during September and October of 2018. In this study, researchers instructed participants to wear a smartwatch (Honor Band 4 wristband or Huawei Watch GT or Honor Watch) for 2 weeks, after which 11 participants were diagnosed with persistent Afib and 20 were diagnosed with paroxysmal Afib. The positive predictive value for Afib for each wearable device was higher than 91%. In addition, demonstrating smartwatch capability to detect different types of heart rhythms, Perino et al[49] found that the irregular pulse detection algorithm in the Apple watch could help detect non-Afib arrhythmias.

In a retrospective, observational cohort study, Feldman et al[28] analyzed wearable and electronic health record data from 1,802 patients wearing an Apple watch, finding that the usefulness of data from a wearable device such as the Apple watch varies by patient cohort. Using only Apple watch data, the study investigators found that approximately 0.25% of the patients in their study population could benefit from an anticoagulation therapy intervention. Studying 419,297 Apple watch Heart application users, Perez et al[48] found that the likelihood of receiving a smartwatch PPG irregular pulse notification was similar to that generated by an ECG patch. However, Wang et al[60] performed a propensity-matched cohort trial involving 16,320 patients with Afib to assess Afib control in patients who used smartwatches compared with those who did not. At the end of the 90-day trial, the researchers found similar heart rates between both the groups of patients.

Tison et al[57] found that, although Apple watch PPG data combined with a neural network can detect Afib, its sensitivity and specificity are less than the gold-standard ECG devices. Preliminary results from the ongoing REMOTE trial (https://clinicaltrials.gov/ct2/show/NCT05006105) suggested that the quality of signals captured using smartwatch is lower than that of signals captured

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by the smartphone (43.4% vs 17.8%, respectively; $P<.001$).[63]

Kinematic Analysis. Five of the 51 studies (9.8%) used gait or other kinematic data to evaluate patients with or at risk of CeVD.

Two studies assessed cognitive-motor performance using the dual-task walking activity in patients with CeVD. Feld et al[27] tracked daily ambulatory activity using a physical activity monitor in chronic poststroke patients, finding that gait speed decreased while performing more attention-demanding tasks. Analogously, Ma et al[43] found that elderly patients with cerebral small vessel disease exhibited lower speed and increased gait variability and asymmetry than healthy control participants under more attention-demanding walking conditions.

Using magnetic resonance imaging (MRI) scans and Sennogait insole insert device activity data, Li et al[42] found that slower walking and shorter stride length were associated with cerebral small vessel disease whereas cerebral microbleeds were associated with longer strides. The pilot study by Park et al[46] validated the use of an insole pressure sensor and accelerometer data for a gait-monitoring stroke prediction algorithm. Instructing participants to perform daily activities, researchers aggregated gait data and applied machine learning algorithms to classify movement, finding the highest classification performance for the C4.5 and support vector machine algorithms with an AUROCC of 0.98 and 0.976, respectively.

Simmatis et al[54] instructed chronic stroke survivors to videorecord facial muscle and speech tasks for 30 days using a Samsung Galaxy Tab A7 tablet application to assess orofacial kinematics (velocity, range of motion, and lateralization). They found the application was an effective remote assessment tool, comparable with in-laboratory 3-dimensional–capable cameras.

Physical Activity. The use of wearable sensors to estimate physical activity was studied in 5 articles (5/51, 9.8%).

Costa et al[25] manually counted the number of steps for chronic poststroke participants completing a walking test who also used the following mHealth tools to automatically measure step count: Google Fit, Health, STEPZ, Pacer, and Fitbit Ultra. Investigators found a statistically significant association for the manually counted steps and the step counts estimated by each mHealth tool. Moreover, no statistically significant difference regarding step count accuracy was observed when an mHealth tool was worn on the paretic or nonparetic side. Comparing step counts recorded by the Garmin Forerunner with patient-reported step counts using the International Physical Activity Questionnaire (IPAQ), Honado et al[33] found high correlations between IPAQ scores and wearable step counts for stroke survivors and healthy controls. Fonte et al[29] found that the ActiGraph WGT3x-BT accelerometers recorded the most accurate data for energy expenditure calculations when worn on the contralateral ankle of chronic poststroke patients.

Several studies assessed the accuracy of step count by digital sensors. Schaffer et al[53] found that step counts of chronic poststroke patients recorded by the Fitbit Zip were both more accurate and reliable than those recorded by the Garmin Vivofit; however, step counts were more accurate for faster walkers. Hui et al[35] used the Fitbit One and Actical accelerometer devices to track physical activity in 12 chronic poststroke patients during a 3-day step count. With both devices worn on the nonparetic ankle for the study duration, step count and light-intensity physical activity were associated ($r>0.90$) for both devices; however, no associations were found for step count and higher-intensity physical activity levels. In addition, the step count data for participants whose walking speeds were at least 0.58 m/s had a lower error (−8.0%) than those with slower walking speeds (27.4%).

Blood Pressure. In a 90-day pilot RCT, researchers evaluated a care model for blood pressure (BP) management using a wearable BP monitor and smartphone application at home.[39] Each day, 50 poststroke participants measured their BP, with 22 participants receiving standard care and 28 participants using the wearable monitor-smartphone system that immediately transmitted readings to clinicians who made appropriate adjustments to participant medication dosages each week.

At study completion, the mean BP declined significantly for participants using the monitor-smartphone system.

Behavioral Monitoring

A few studies (4/89, 4.5%) assessed the use of digital sensors for monitoring behavioral variables in patients at risk of or diagnosed with CeVD.

Fatigue. Lenaert et al[68] used the PsyMate application to collect real-time data on fatigue experienced by poststroke patients who completed 10 daily questionnaires using their smartphone touchscreen sensors to select answers. At the end of the 6-day assessment, participants completed the standard Fatigue Severity Scale (FSS) survey. Investigators found a range of Pearson correlation coefficients between momentary fatigue assessments and FSS scores (range, 0.334-0.667) and that patients with identical FSS scores experienced daily fatigue differently.

Mood. In the pilot study by Forster et al[66] in 2020, a neuropsychological assessment technique was administered using the movisensXS app on the Android Motorola Moto G smartphone to 15 patients with acquired brain injury, some of whom were chronic stroke survivors. The technique, described as ecologic momentary assessment (EMA), consisted of prompting participants to complete 8 surveys per day, for 7 days, tracking current activities, social context, mood, self-judgments of individual functional status, and self-reflection frequency. Researchers found high adherence with the study protocol (71.6%) and consistent within-person response variability (44.9%) regardless of patient age, depression severity, or level of functioning. The second study by Forster et al,[65] in 2022, focused on poststroke patients using the same smartphone application system and a similar protocol. Researchers found that self-reported functionality and mood were closely associated for an individual EMA survey; however, only participant mood was predictive of self-reported functionality at the next EMA survey.

Cognitive Function. To assess cognitive function in 12 chronic poststroke patients, Jung et al[67] aggregated performance data from Neuro-World, a software game estimating the mini-mental state examination. Comparing game performance between baseline and 90 days, researchers built a machine learning model to estimate mini-mental state examination scores at 90 days with a high degree of accuracy (root mean squared error of 5.75%).

DISCUSSION

The primary outcome of this scoping review was the characterization of 51 studies examining digital sensors in wearable devices and smartphones to track physiologic and behavioral signals relevant to CeVD monitoring. The analysis of the studies generated a map of digital sensors, devices, and smartphones available to monitor and, in some cases, detect patients diagnosed with or at risk of CeVD. Most studies used a PPG-enabled or ECG-enabled smartwatch, wrist-worn accelerometer or smartphone application to collect signal data. Most studies (30/51, 58.8%) were published after 2019, suggesting that research evidence is preliminary.

The findings of this review suggest that digital sensors in wearable devices and smartphones have the potential to monitor gait and physical activity associated with emerging neurological deficits after stroke. These tools can also augment clinical diagnosis of CeVD-related disability more precisely and discriminate between physical activity data from healthy participants and poststroke patients; however, for algorithms detecting physical activity, movement classification becomes increasingly difficult because patient activities become more complex in real-world settings. The use of wearable devices to monitor heart rhythm was linked with an increased likelihood of timelier detection of Afib, and the accuracy of Afib detection on the basis of heart rate using smartwatches and smartphone applications was comparable with the costlier standard: the Holter monitor. In addition, the transmission of remote monitoring BP data by poststroke patients to clinicians for frequent medication adjustments has been reported to significantly improve BP. While interactive software games can be used to

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predict a patient's cognitive function, smartphone-based surveys can provide insights into changes in mood and fatigue.

The sensors evaluated in these studies found sufficient sensitivity to detect abnormal signals; however, their translation into clinical practice is limited by their current inability to discriminate one CeVD type from another, lacking the capability to correlate a signal abnormality with a specific etiology. Although wearable and smartphone-based digital sensors can generate reliable data related to CeVD status, the need for investigation of any signal abnormality by a clinician is vital to ensuring patient safety and minimizing provider liability.

The diagnostic accuracy linked to data obtained from a digital sensor is dependent on the quality of sensors. With most camera, microphone, and touchscreen sensor studies reporting highly accurate results, modern smartphone sensors seem to be of high enough quality for diagnostic purposes. Because this was not a systematic review, the signal quality and parameters associated with each device studied in this review were not assessed, a limitation that could have affected conclusions drawn from the summarized evidence.

One limitation of this study is the dearth of rigorous evaluation studies related to monitoring patients with or at risk of CeVD in real-world settings. Only 13.7% (7/51) of the included studies used a clinical trial design. Most studies (23/51, 45.1%) were small pilot studies with an average of 45.3 participants. Moreover, most participants across studies were White and male. Another limitation is that 35.3% (18/51) of the studies did not specify the type of CeVD, such as IS or HS, studied. Sixteen (31.4%) did not conduct separate analyses for patients with distinct CeVD types. No studies examined diagnoses of branch retinal artery occlusion or CRAO, vascular dementia or multi-infarct dementia. Regarding the feasibility of monitoring, more than 25% of participants were lost to follow-up in clinical trial and longitudinal cohort studies.[31,45] Combined with limited information about patient CeVD diagnoses in most studies, no conclusion can be drawn regarding optimal participant demographic characteristics or sampling time points, such as before or after a diagnosis, for designing CeVD monitoring programs that yield clinically meaningful results, particularly when primary stroke patients are categorized with patients at risk of a first stroke.

CONCLUSION

This scoping review presents a robust assessment of the literature on the use of wearable and smartphone-based digital sensors for monitoring of patients at risk of or diagnosed with CeVD. We identified variable methods and conclusions associated with wearable and smartphone digital sensors in CeVD. Although most articles assessed pilot studies, only a few relevant RCTs have been published, highlighting a major gap in the literature. The following conclusions were drawn: (1) wearable and smartphone digital sensors have the potential to augment in-person and facilitate remote diagnoses of CeVD; (2) data from digital sensors report promise regarding the potential prediction of stroke based on abnormal signals; and (3) wearable and smartphone digital sensors have the potential to screen, detect, or grade the severity of CeVD-related clinical sequelae, for example, cognitive impairment, fatigue, depression, or falls. Given that smartphones and wearable devices are more frequently used than ever before, integrating digital sensor monitors in clinical research represents a growing opportunity to personalize care and increase access to specialists. Future research should investigate distinct types of CeVD without conflating diagnostic categories, prioritize larger cohorts of more diverse participants, and compare *in situ* monitoring data with that collected in controlled settings. The information summarized in this study serves as a roadmap to inform the development of future trials and systematic reviews investigating the risk of bias in evidence related to this field.

POTENTIAL COMPETING INTEREST

Given their role as Editorial Board Members, B.J.E. and B.M.D. were not involved in the peer-review of this article, with no access to information regarding its peer-review. All other authors report no competing interests.

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SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at https://www.mcpdigitalhealth.org/. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data.

Abbreviations and Acronyms: **Afib,** atrial fibrillation; **AUROCC,** area under the receiving operating characteristic curve; **BP,** blood pressure; **CeVD,** cerebrovascular disease; **CRAO,** central retinal artery occlusion; **CS,** cryptogenic stroke; **ECG,** electrocardiogram; **EMA,** ecologic momentary assessment; **FSS,** Fatigue Severity Scale; **HS,** hemorrhagic stroke; **IS,** ischemic stroke; **PPG,** photoplethysmogram; **RCT,** randomized controlled trial; **TIA,** transient ischemic attack; **UL,** upper limb

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