ESC European Heart Journal - Digital Health (2026) 7, ztag074
https://doi.org/10.1093/ehjdh/ztag074

REVIEW

Digital biomarkers in cardiovascular medicine: a scientific statement of the ESC Working Group on e-Cardiology, the ESC Working Group on Cardiovascular Pharmacotherapy, the European Heart Rhythm Association (EHRA) of the ESC, the Association for Acute Cardiovascular Care (ACVC) of the ESC, the Heart Failure Association (HFA) of the ESC, the European Association of Preventive Cardiology (EAPC) of the ESC, the European Association of Cardiovascular Imaging (EACVI) of the ESC, in collaboration with the Digital Cardiology and Artificial Intelligence Committee of the ESC, and the ESC Regulatory Affairs Committee

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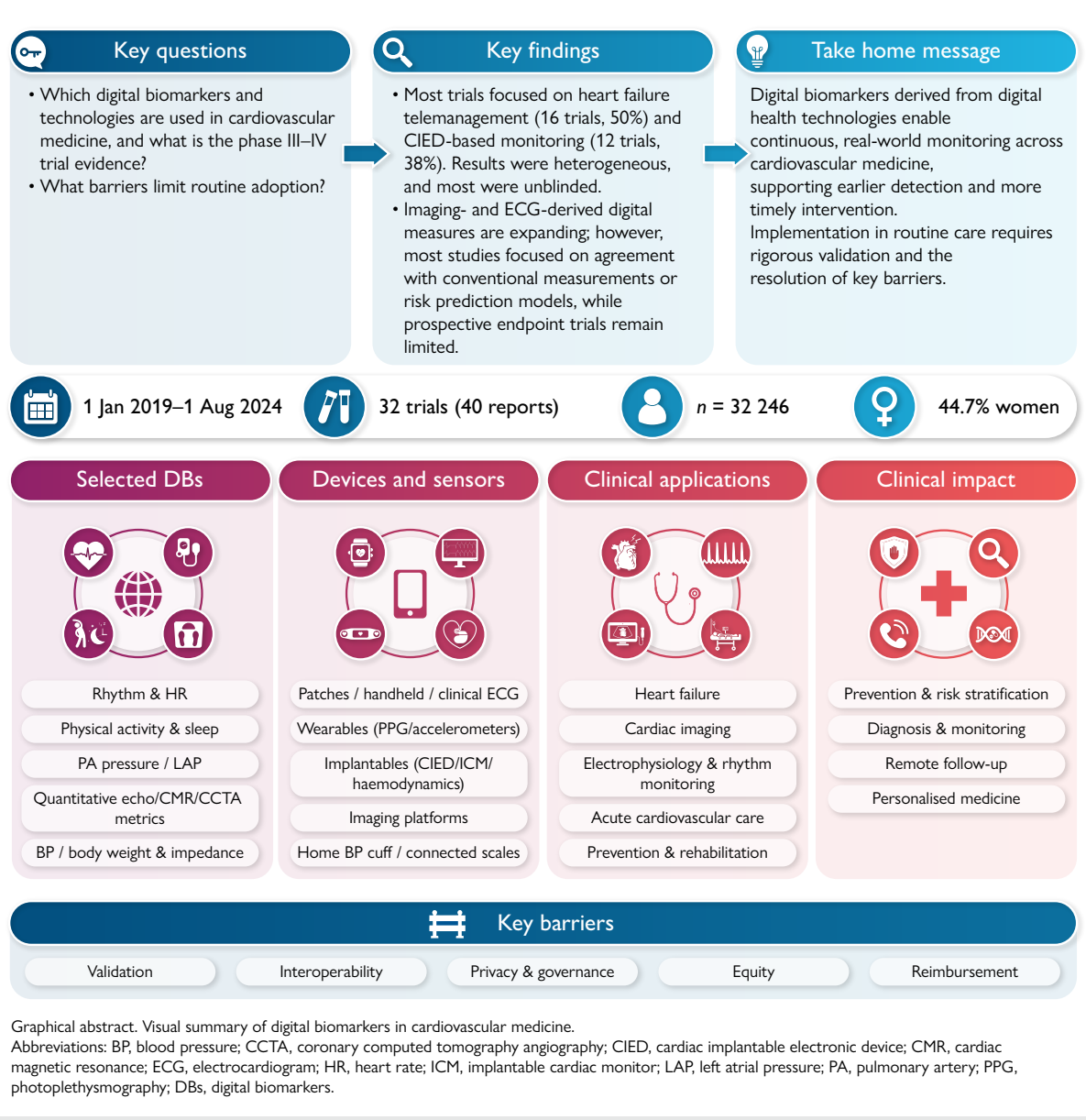
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Received 7 November 2025; revised 16 February 2026; accepted 2 April 2026; online publish-ahead-of-print 17 July 2026

Cardiovascular disease is the leading cause of morbidity and mortality globally, imposing a substantial patient burden. Digital biomarkers derived from digital health technologies enable quantifiable, near-continuous, real-world capture of pathophysiological signals and are increasingly used across cardiovascular medicine. Their growth is often supported by big data analytics, artificial intelligence and connected sensors within the Internet of Things. This scientific statement systematically reviews digital biomarkers, their clinical utility across the cardiovascular care continuum, and summarizes major methodological and implementation challenges. We searched PubMed/MEDLINE, Embase and Scopus for phase III–IV cardiovascular trials published between 1 January 2019 and 1 August 2024 that collected digital biomarkers. We identified 541 records and included 32 trials (40 reports) enrolling 32 246 participants (44.71% women; mean age 66.2 ± 11.0 years). Heart failure was the most frequent target condition (16 trials, 50%), followed by cardiac implantable electronic devices trials (12 trials, 38%). Digital biomarkers included cardiac rhythm and heart rate, blood pressure, body weight, impedance-based measures, haemodynamic pressures, and physical activity and sleep patterns captured using diverse sensor technologies. Methodological quality was good (modal quality score 5; range 3–7), although most trials were unblinded. Current studies suggest potential clinical utility in selected cardiovascular conditions. Implementation remains challenging because of measurement variability, privacy and regulatory requirements, affordability and reimbursement barriers and inequities in access. Robust validation and outcome- and cost-effectiveness evidence are still needed. Registration number: CRD42024573879.

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Graphical abstract



Graphical abstract. Visual summary of digital biomarkers in cardiovascular medicine.
Abbreviations: BP, blood pressure; CCTA, coronary computed tomography angiography; CIED, cardiac implantable electronic device; CMR, cardiac magnetic resonance; ECG, electrocardiogram; HR, heart rate; ICM, implantable cardiac monitor; LAP, left atrial pressure; PA, pulmonary artery; PPG, photoplethysmography; DBs, digital biomarkers.

Visual summary of digital biomarkers in cardiovascular medicine and key barriers to implementation.

Keywords Digital biomarkers • Digital health technology • Cardiovascular system • Wearable devices • Telemonitoring • Systematic review

Introduction

Cardiovascular disease (CVD) remains the leading cause of morbidity and mortality worldwide, burdening patients with multiple debilitating symptoms. CVD diminishes workforce productivity and imposes substantial economic burdens due to high treatment costs and hospitalizations. Digital health technologies (DHTs) have the potential to solve the challenges within global healthcare systems. They may enhance early detection, optimize treatment, reduce disparities in access and lower overall healthcare costs, while improving quality of life and outcomes.[1,2]

Biomarkers are frequently used in clinical practice, both in hospital and after discharge, as well as in medical research. Both the European Medicines Agency (EMA) and the US Food and Drug Administration–National Institutes of Health (FDA–NIH) Biomarker Working Group define a biomarker as an objective, quantifiable characteristic that reflects normal biological processes, pathogenic processes or responses to exposures or interventions, excluding measures of how an individual feels or functions.[3,4] Biomarkers can be classified based on their function into overlapping categories: Risk/susceptibility, diagnostic, monitoring, prognostic, predictive, pharmacodynamic/response,

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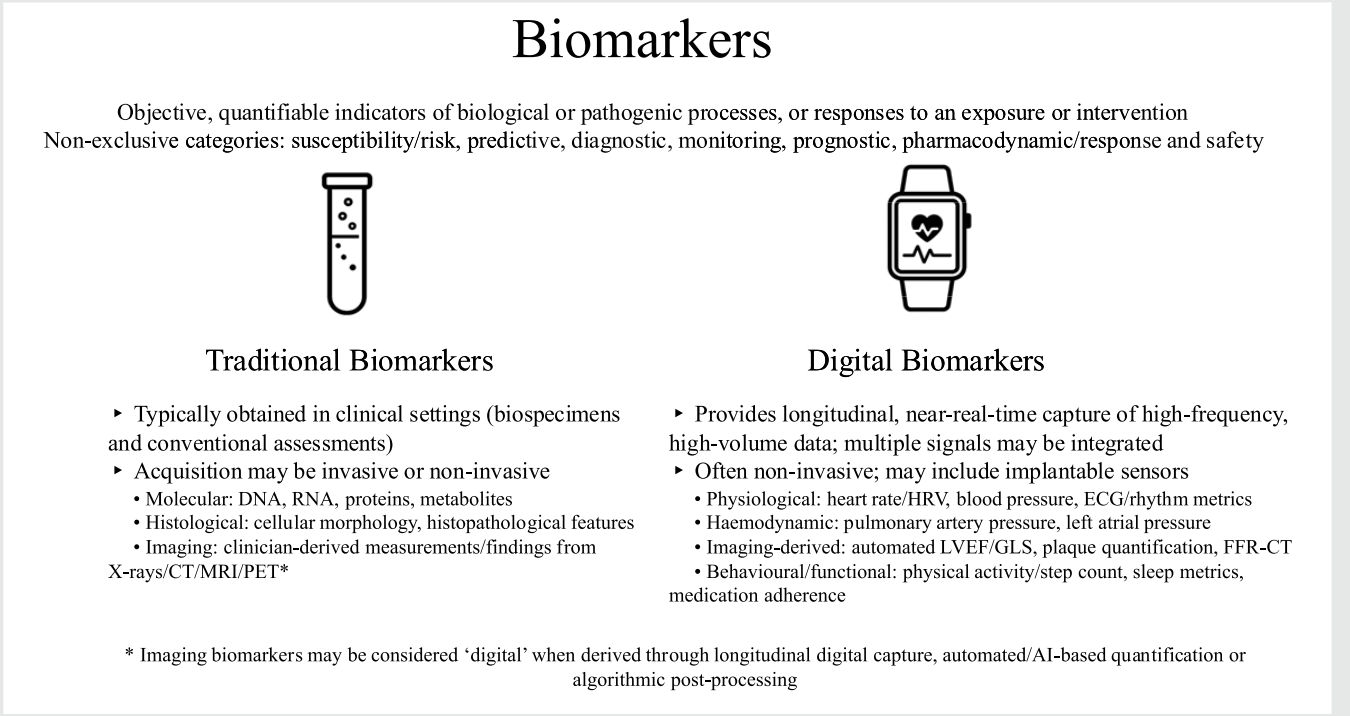


Figure 1 Traditional vs. digital biomarkers. Traditional biomarkers are typically obtained in clinical settings and provide episodic measurements (e.g. molecular, histological and imaging findings). Digital biomarkers are derived from digital health technologies and algorithms and are often captured longitudinally in near real time, generating high-frequency, high-volume data (e.g. physiological and haemodynamic signals, imaging-derived metrics and behavioural measures). Imaging may be considered 'digital' when derived through automated/AI-based quantification or algorithmic post-processing. Abbreviations: DNA, deoxyribonucleic acid; RNA, ribonucleic acid; CT, computed tomography; MRI, magnetic resonance imaging; PET, positron emission tomography; LVEF, left ventricular ejection fraction; GLS, global longitudinal strain; FFR-CT, fractional flow reserve computed tomography; ECG, electrocardiography; HRV, heart rate variability.

and safety biomarkers.[4,5] According to the EMA, the clinical relevance of biomarkers requires a reliable association with validated clinical endpoints.[6]

Digital biomarkers (DBs) are biomarkers derived from data captured by DHTs, processed, and stored using digital tools.[7] However, definitions of DBs remain heterogeneous in the biomedical literature. Despite this variability, DBs typically share common characteristics. They are often acquired non-invasively, collected longitudinally in near real time, and are characterized by high sampling rates, high data volume and algorithm-based processing.[8] Moreover, multiple signals can be captured concurrently and integrated into a composite DB.[9] Nevertheless, there can be overlap between traditional biomarkers and DBs, particularly when measurements are digitally captured and processed (*Figure 1*).

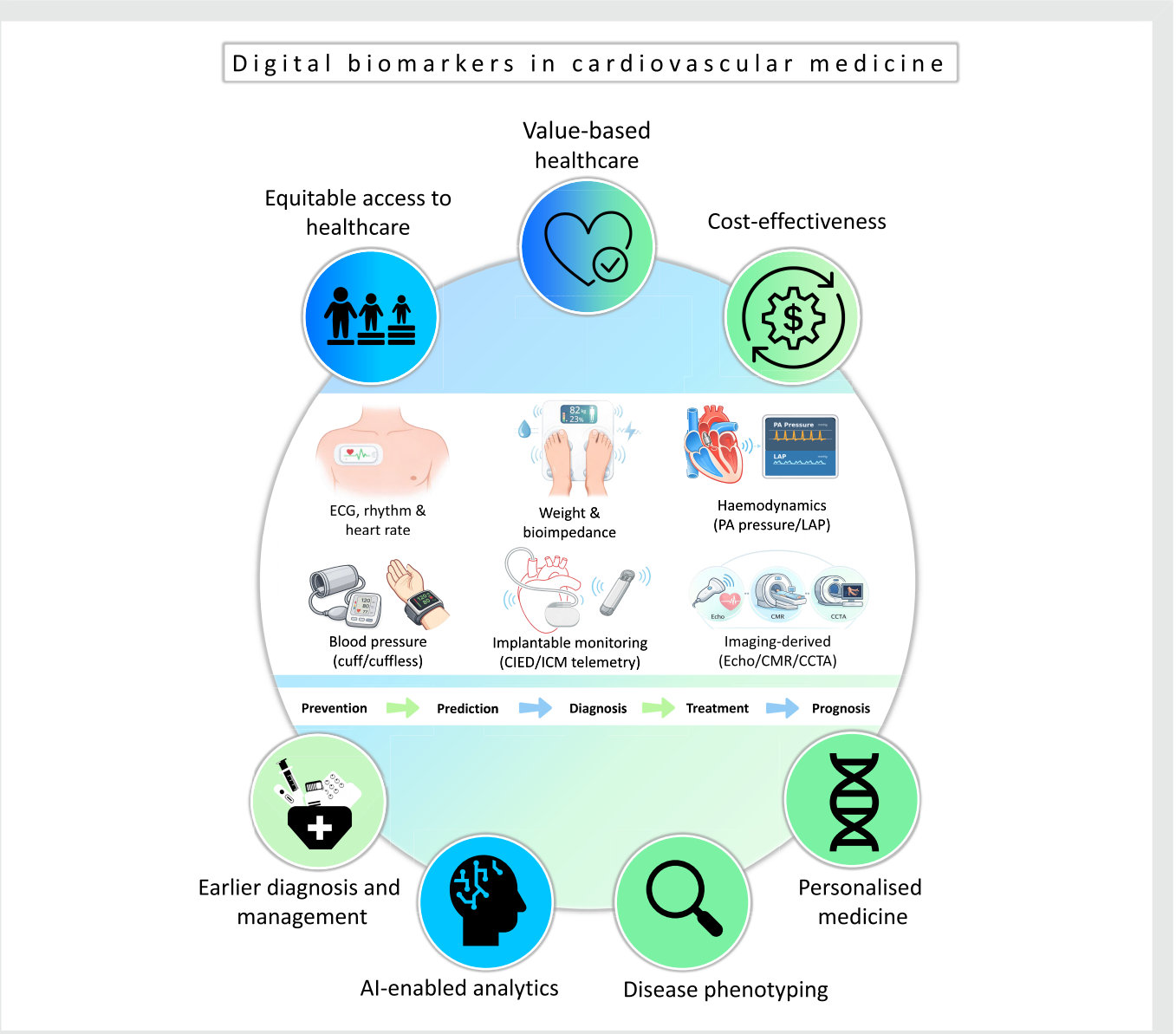
Mobile health (mHealth, smartphone, and wearable health applications) and the Internet of Things (connected sensors and devices) enable early, extensive remote capture and transmission of signals to clinical dashboards for evaluation and management. Big data analytics and artificial intelligence (AI) can derive DBs from these signals to support disease phenotyping, risk prediction and personalized medicine. The widespread use of consumer DHTs facilitates the collection of DBs in real-world, naturalistic environments and may promote more equitable access to care. Patient empowerment through DHTs may facilitate a shift towards more proactive care and self-management, in line with the goals of value-based healthcare. In parallel, DBs are increasingly being incorporated into clinical trials (CTs) with decentralized trial designs and continuous endpoint capture, improving trial efficiency and accelerating the evaluation of novel therapies.[10,11]

Although the term 'digital biomarker' is not yet widely used, measurements obtained using DHTs are already applied in cardiology across prevention, prediction, diagnosis, treatment, and prognosis. For example, DBs range from blood pressure trends to metrics derived from remote monitoring of cardiac implantable electronic devices (CIEDs) (see Central illustration).

However, integrating DBs into clinical practice and research remains challenging. Despite major technological advances in cardiovascular medicine, there is still substantial variability in measurement accuracy across devices and algorithms. Additionally, the legal and regulatory framework is still evolving, particularly regarding the standardization of validation processes and compliance with data protection and privacy requirements across clinical and consumer settings, which complicates widespread adoption of DBs. Moreover, heterogeneous access to DHTs and the failure to establish clear reimbursement programmes remain substantial barriers, even in well-resourced healthcare systems, and may be further exacerbated by socioeconomic and cultural factors.[12,13]

Given the rapid advances in DHTs and the exponential growth of available DBs, this paper aims to summarize the current clinical applications and associated technologies of DBs across cardiology subspecialties. It also outlines key considerations in DB

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Central illustration Digital biomarkers (DBs) in cardiovascular medicine include measurements such as electrocardiography, cardiac rhythm and heart rate, blood pressure, body weight and impedance-based measures, cardiac implantable electronic device/implantable cardiac monitor telemetry, haemodynamics including pulmonary artery pressure and left atrial pressure, and imaging-derived DBs from echocardiography (Echo), cardiac magnetic resonance, and coronary computed tomography angiography. DBs are captured using invasive and non-invasive digital health technologies and are used across the clinical continuum from prevention and risk prediction to diagnosis, treatment monitoring, and prognostication. DBs can support disease phenotyping and personalized care, helping enable earlier detection and intervention and thereby contributing to value-based, cost-effective, and more equitable healthcare. Their role is expected to expand further as AI-enabled analytics continue to evolve.

development and validation, including methodological, regulatory, and implementation barriers.

Methods

Search strategy

A structured literature search was performed in PubMed/MEDLINE, Embase and Scopus, covering the period from 1 January 2019 to 1 August 2024 (inclusive). We focused on studies published from 2019 onward because the volume of research on DBs in cardiovascular medicine increased substantially during this period, with peak publication volume observed in 2022. Search terms incorporated controlled terms [Medical Subject Headings (MeSH)/Emtree] and free-text keywords related to DBs and DHTs (e.g. digital biomarker*, digital technolog*, digital tool*, wearable sensor*, remote monitor*) together with cardiovascular terms (e.g. heart, cardiovascular system, heart diseases, cardiology, heart failure, hypertension, coronary artery disease, cardiovascular diseases). Boolean operators were applied, and truncation (*) was used to maximize sensitivity. Trial filters and publication date limits were applied. The full search strings for each database are provided in the Supplementary material online, Appendix *S1*. The review protocol was registered in the

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International Prospective Register of Systematic Reviews (PROSPERO; CRD42024573879). The review was conducted and reported in accordance with the Cochrane Collaboration guidance and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.[14]

Eligibility criteria

The inclusion and exclusion criteria were as follows.

Inclusion criteria

- Studies were phase III or IV CTs.
- DBs were derived from data captured by DHTs.
- The clinical focus was cardiology/cardiovascular medicine.
- Studies were published between 1 January 2019 and 1 August 2024 (inclusive).
- Full-text articles were available in English.

Exclusion criteria

- Phase I–II CTs; preclinical studies; and studies using non-human samples.
- CT protocols and design/rationale/implementation articles; observational studies; systematic reviews/meta-analyses; letters; editorials; expert opinion pieces; and conference abstracts/presentations.
- Studies primarily focused on stroke/cerebrovascular disease, diabetes mellitus, obstetric disorders, or congenital cardiovascular disorders.
- Studies with insufficient reporting to evaluate the DB, intervention or outcomes (e.g. unclear DB definition, missing key trial details, or incomplete outcome data).
- CTs scoring <5 on the seven-item modified Jadad scale (0–7), unless clinically relevant and non-substitutable.

Study selection

Two authors (P.M.C. and R.C.A.) independently screened titles and abstracts and subsequently assessed full texts to identify studies meeting the eligibility criteria. Eligibility was confirmed at full-text review, including restriction to phase III–IV CTs. Discrepancies were resolved by discussion, with reference to the original articles, and, when necessary, through adjudication by a third reviewer.

Data extraction

Data were extracted independently by two authors (P.M.C. and R.C.A.) using a predefined data-extraction form. Extracted variables included first author, year of publication, CT registration number and study acronym (when available), country of enrolment, participant age (mean ± standard deviation [SD] or median [interquartile range (IQR)]), sample size (screened and randomized), sex, population characteristics, DHTs and corresponding DBs, sensor technology, trial objectives/endpoints, key results, and additional comments.

Data availability

No new data were generated or analysed in support of this article. All data underlying this article are included in the main manuscript, its supplementary material and the referenced literature.

Risk of bias and quality assessment

Methodological quality of included CTs was assessed using the seven-item modified Jadad scale. This tool was selected because it provides a pragmatic and reproducible appraisal of key trial features (randomization, blinding, and participant flow). We used the modified version because the original adverse effects item was not applicable, as most included CTs were measurement/monitoring studies and did not systematically report safety outcomes. Quality appraisal was performed by one reviewer and verified by a second. Disagreements were resolved by consensus or, when required, by discussion with a third reviewer. CTs scoring ≥5 (0–7) were considered high quality and were included. In line with the eligibility criteria, the exception for trials scoring <5 was applied. Details of the quality assessment and scoring are reported in the Supplementary material online, Appendix *S2*.

Results

A total of 541 records were identified from three electronic databases. Duplicates (n = 187), non-English records (n = 2), and one record retracted by the publisher (n = 1) were removed prior to screening. Subsequently, 351 records were screened by title and abstract, and 191 records were excluded at this stage. After title/abstract screening, 160 reports were sought for retrieval, 12 could not be retrieved. Overall, 148 full-text articles were assessed for eligibility. Of these, 108 were excluded for the following reasons: study designs other than phase III or IV CTs (n = 49), outside the scope of cardiology (n = 37), use of DHTs primarily for behavioural change (digital therapeutics) rather than DB capture (n = 9), not related to DBs (n = 9) or not using DHTs (n = 4). Among the studies excluded as outside the scope of cardiology, stroke/cerebrovascular disease (n = 19), diabetes mellitus/diabetic foot (n = 6), pregnancy-related or congenital cardiovascular conditions (n = 6), and other reasons (n = 6) were the main topics related to the cardiovascular system but not focused on cardiology. Finally, 32 CTs (40 reports) met the inclusion criteria and were included in the systematic review. The PRISMA flow diagram is presented in *Figure 2*.

Study and population characteristics are summarized in *Table 1* (40 reports corresponding to 32 CTs). Across the 32 CTs, 30 trials were randomized and 2 were single-arm. In total, 32 246 participants were enrolled, including 14 417 women (44.71%). No trial enrolled healthy volunteers. Among studies reporting mean ± SD, the sample size–weighted mean age was 66.2 years (pooled SD, 11.0 years). Across studies and trial arms, median age ranged from 59 to 74 years with the first and third quartiles ranging from 53–67 years and 66–80 years, respectively. Geographically, nine CTs were conducted in the USA, with the remaining trials undertaken across 10 other countries, including six multinational studies. Most participants [29 666 (92%)] were enrolled in studies conducted in the USA, China, the UK, Poland, Japan, or multinational settings (see Supplementary material online, *Figure S3*).

Table 1 summarizes the characteristics of the included studies. Heart failure (HF) was the primary condition studied in 16 CTs (50%). These studies evaluated remote monitoring and telemanagement in both heart failure with reduced ejection fraction (HFrEF) and heart failure with preserved ejection fraction (HFpEF) using a range of devices. Some approaches were non-invasive, capturing data such as body weight, bioimpedance measurements, blood pressure (BP), electrocardiography (ECG) and physical activity/exercise metrics. Others relied on invasive or implantable systems, including measurements obtained from CIEDs, pulmonary artery (PA) pressure waveforms, and left atrial pressure (LAP). Outcomes assessed included quality of life, changes in biomarker levels [e.g. N-terminal pro-B-type natriuretic peptide (NT-proBNP)], the efficacy and safety of haemodynamic-guided HF management with CardioMEMS™ or V-LAP™ monitoring, reductions in major adverse cardiovascular events (MACE)—particularly HF hospitalizations—and digital health literacy related to HF devices.

Additionally, CIEDs were used in 12 CTs (38%). Within CIED-based CTs, pacemakers/cardiac resynchronization therapy pacemakers (CRT-P) were included in 3 (25%) and implantable cardioverter-defibrillators (ICDs)/cardiac resynchronization therapy defibrillators (CRT-D) in 6 (50%); the remaining 3 (25%) involved mixed device cohorts or did not specify device type. Remote monitoring was delivered through manufacturer-specific

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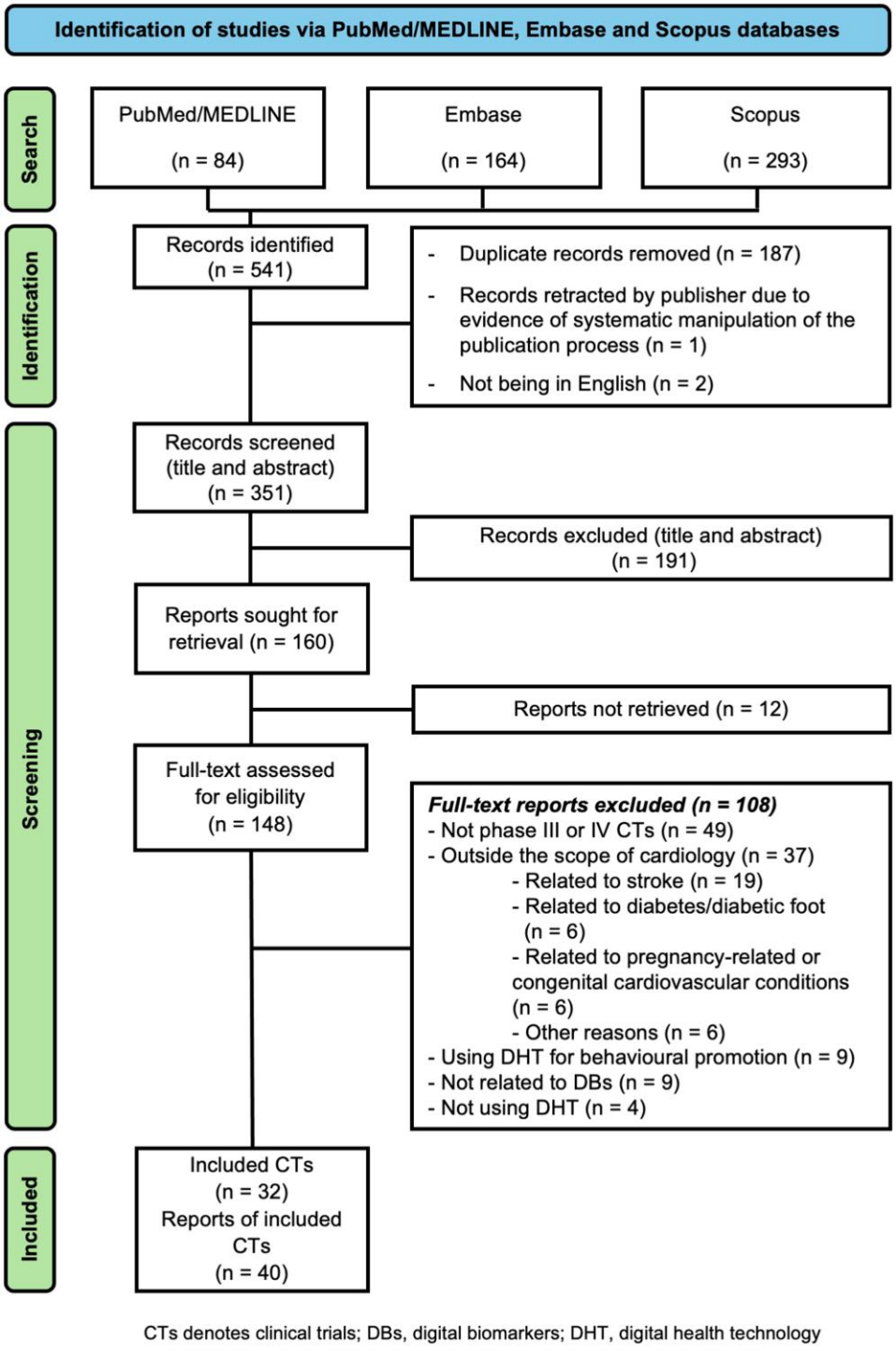


Figure 2 PRISMA flow diagram in four levels.

platforms (e.g. Biotronik Home Monitoring/CardioMessenger, Boston Scientific LATITUDE, Abbott/St. Jude Merlin.net and Medtronic CareLink), sometimes within the same trial depending on the implanted device. Most reports specified device type and/or the remote monitoring platform but rarely reported the exact CIED model.

Excluding CIEDs, 38 device uses were reported across the included CTs, corresponding to 33 distinct device models (manufacturer and model). These DHTs were grouped into eight device categories, with the number of distinct device models in parentheses: weight scales (9), wearable/portable ECG monitors (8), implantable cardiac monitors (ICMs) (4), step counters/

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Table 1 Characteristics of 40 reports corresponding to 32 phase III–IV clinical trials that evaluated cardiovascular digital biomarkers derived from digital health technologies. Reports are listed in reverse chronological order

First author (year)	Clinical trial registration number (study abbreviation)	Country of enrolment	Age, years [mean ± SD or median (IQR)]	Screened sample	Randomized sample	Women, %	Population characteristics	Digital health technologies (digital biomarkers)	Sensor technology	Objective	Results	Comments
Victoria-Castro (2024)[15]	NCT04394754	USA	61 [53–69]	182	182	37.9	HFpEF or HFrEF	**Bodyport cardiac scale** (HR; body weight; bioimpedance)	ECG; ballistocardiogram; impedance plethysmogram signals	Evaluate the 90-day change in quality of life (KCCQ-OSS)	No significant change in KCCQ-OSS, and no improvement vs. usual care	The intervention used Conversa (conversational platform) and Noom (smartphone app); at 90 days, symptoms and physical function improved significantly in the Noom arm
Jøns (2024)[16]	NCT02341534 (BIO-GUARD-MI)	Multinational (USA, Australia, Austria, Belgium, Czech Republic, Denmark, France, Germany, Hungary, Latvia, Netherlands, Poland, Slovakia, Spain)	71.2 ± 8.1	802	790	28	ACS and a CHA_2DS_2-VASc score ≥4 (men) or ≥5 (women), LVEF > 35%	**BioMonitor 2-AF (ICM)** (cardiac rhythm; arrhythmia detection; HR); **BIOMONITOR III (ICM)** (cardiac rhythm; arrhythmia detection; HR)	ECG	Evaluate whether arrhythmia monitoring with an ICM improves treatment and outcomes	Asymptomatic but actionable arrhythmias were common post-infarction; however, ICM monitoring did not improve outcomes in the overall cohort	Post-hoc analyses suggested potential benefit in non-ST-segment elevation myocardial infarction patients and other high-risk subgroups
Gomez (2024)[17]	NCT05366803 (WHISH STAR)[a]	USA	78.8 ± 4.3	4791	1257	100	Postmenopausal women with 5-year predicted risk of incident AF ≥ 5% by CHARGE-AF score	**Single-lead ECG patch** (cardiac rhythm; arrhythmia detection; HR)	ECG	Determine the prevalence of frequent premature ventricular contractions and non-sustained ventricular tachycardia	Premature ventricular contractions were relatively common (4.3%) and were associated with higher CHARGE-AF scores	Seven-day ECG patch screening was performed at baseline, 6 months and 12 months
Alshahrani (2024)[18]	NCT05015634 (TELE-ACS)	UK	Intervention 57.6 ± 8.7; Control 58.6 ± 9.7	372	337	13.9	ACS with percutaneous coronary intervention and at least one cardiovascular risk factor	**SmartHeart ECG belt (12-lead)** (cardiac rhythm; arrhythmia detection; HR)	ECG	Evaluate time to first readmission at 6 months	Readmissions were reduced over 6 months (HR 0.24; 95% CI 0.13–0.44; $P < 0.001$)	Telemedicine-based post-ACS care reduced readmissions, emergency department visits

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Table 1 *Continued*

First author (year)	Clinical trial registration number (study abbreviation)	Country of enrolment	Age, years [mean ± SD or median (IQR)]	Screened sample	Randomized sample	Women, %	Population characteristics	Digital health technologies (digital biomarkers)	Sensor technology	Objective	Results	Comments
												and unplanned revascularization and improved symptoms
Chin-Sheng Lin (2024)[19]	NCT05118035	China	61.2 ± 18.3	16 335	16 335	47.3	Emergency and inpatient patients	**AI-enabled ECG** (cardiac rhythm; arrhythmia detection; HR)	ECG	Identify hospitalized patients at high risk of mortality	The AI-ECG alert was associated with reduced all-cause mortality (HR 0.83; 95% CI 0.70–0.99)	The mechanisms by which the AI-ECG alert reduced mortality remain to be fully elucidated
Stolen (2023)[20]	NCT04732728 (LUX-Dx PERFORM)	USA	65.8 ± 14.6	369	—[h]	49.9	ICM implantation	**LUX-Dx™ ICM** (cardiac rhythm; arrhythmia detection; HR)	ECG	Characterise ICM remote monitoring rates	High data transmission rates, detection of atrial flutter and feasibility of remote programming	
Nassif (2023)[21]	NCT03030222 (EMBRACE-HF)	USA	66.2 ± 12.9	93	65	37	HFpEF or HFrEF and an elevated PA diastolic pressure	**CardioMEMS™** (PA pressure)	MEMS	Evaluate change in NT-proBNP from baseline	Short-term reductions in ambulatory PA diastolic pressure were associated with reductions in NT-proBNP	
Kronborg (2023)[22]	(DANPACE II trial)	Denmark	DDR-60 73 [67–79]; DDD-40 74 [67–80]	540	539	DDR-60 48; DDD-40 52	Sinus node dysfunction with a first-time pacemaker implantation	**RM platforms (Biotronik; Boston Scientific; Medtronic; Abbott)** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate whether atrial pacing minimization in sinus node dysfunction reduces the incidence of AF	Atrial pacing minimization did not reduce AF incidence; a base rate of 40 bpm without rate adaptation increased syncope/presyncope risk	
Ginder (2023)[23]	NCT00559988 (IMPACT)	Multinational (USA, Australia, Canada, Denmark, Germany, UK)	64.4 ± 11.5	4226	2718	26.3	ICD/CRT-D, $CHADS_2$ risk score ≥1 and ability to tolerate anticoagulation	**RM platform** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate the composite endpoint of stroke, systemic embolism and major bleeding	Anticoagulation initiation/ interruption based on remotely detected atrial tachyarrhythmias did not prevent thromboembolism or bleeding	
Desai (2023)[24]	NCT03387813 (GUIDE-HF)	Multinational (USA, Canada)	HF hospitalization in Previous Year 67.6 ± 11.6, Elevated natriuretic	1000	999	HF hospitalization in Previous Year 39.7, Elevated natriuretic peptides Only 34.6	NYHA II-IV HF and either previous HF hospitalization or elevated natriuretic peptides levels	**CardioMEMS™** (PA pressure)	MEMS	Evaluate the efficacy and safety of haemodynamic-guided HF management in patients with elevated natriuretic peptides	Haemodynamic-guided HF management supports consideration in chronic HF with elevated natriuretic	

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Table 1 *Continued*

First author (year)	Clinical trial registration number (study abbreviation)	Country of enrolment	Age, years [mean ± SD or median (IQR)]	Screened sample	Randomized sample	Women, %	Population characteristics	Digital health technologies (digital biomarkers)	Sensor technology	Objective	Results	Comments
			peptides Only 71.2 ± 9.9							but no recent HF hospitalization	peptides and no recent HF hospitalization	
D'Amario (2023)[25]	NCT03775161 (VECTOR-HF)	Multinational (Germany, Italy)	71.50 [63.75–75.75]	30	—[h]	23.3	HFpEF or HFrEF with optimal medical and device therapy in NYHA Functional Class III	**V-LAP™ system** (left atrial pressure)	MEMS	Evaluate device deployment, feasibility of measurements and freedom from major adverse cardiac and neurological events through 3 months post-procedure	Generally safe, with good correlation vs. invasive pulmonary capillary wedge pressure; early evidence suggested possible symptom improvement	
Wita (2022)[26]	NR	Poland	66.1 ± 10.5	NR	60	21.7	HFrEF with CRT-P/CRT-D	**BP monitor** (BP); **3-lead ECG recorder** (cardiac rhythm; HR); **weight scale** (body weight)	NR	Evaluate whether telemedicine devices reduce the composite endpoint of death or first emergency hospitalization	Telemonitoring in CRT recipients improved 2-year prognosis and reduced HF hospitalization	
Spindler (2022)[27]	NCT03388918	Denmark	Intervention 61.73 ± 10.75; Control 61.36 ± 11.46	353	137	Intervention 24; Control 23	HF with NYHA I-IV, of whom a maximum of 20% of the patients were of NYHA class I, ≥18 years of age	**UA-767PBT BP monitor** (BP); **UC-321PBT weight scale** (body weight); **Fitbit Zip** (physical activity); **Fitbit Charge** (physical activity; sleep metrics); **Beddit 3** (sleep metrics)	Oscillometry (UA-767PBT BP monitor); strain-gauge load cell (UC-321PBT weight scale); accelerometer (Fitbit Zip; Fitbit Charge); PPG (Fitbit Charge); piezoelectric sensor (Beddit 3)	Evaluate changes over time in eHealth Literacy Questionnaire in HF patients in a telerehabilitation programme vs. a traditional rehabilitation programme	A digital toolbox to support health information processing in HF may improve eHealth Literacy Questionnaire scores, motivation and engagement with digital services	
Piotrowicz (2022)[28]	NCT02523560 (TELEREH-HF)[b]	Poland	Intervention 62.7 ± 10.5; Control 62.3 ± 10.1	2333	850	Intervention 11; Control 11.8	HFrEF with NYHA I-III after a cardiovascular hospitalization within the 6 months before randomization	**EHO mini device-ECG** (cardiac rhythm; HR); **BP monitor** (BP); **weight scale** (body weight)	ECG; NR (BP monitor; weight scale)	Evaluate the influence of HCTR on depressive symptoms and physical capacity in HF	HCTR produced similar reductions in depressive symptoms to usual care and improved physical capacity in patients with and without depression	
Treskes (2022)[29]	NCT02976376 (TheBox)	Netherlands	59 [53–66]	NR	200	32	ACS with more than 90% occlusion on coronary angiography (≤48 h after onset of symptoms)	**Withings ecosystem: scale** (body weight), **BP monitor** (BP), **Pulse Ox** (oxygen saturation); **KardiaMobile (single-lead)** (cardiac rhythm; arrhythmia detection; HR)	Strain-gauge load cell (Withings scale); oscillometry (Withings BP monitor); PPG + accelerometer (Withings Pulse Ox); ECG (KardiaMobile)	Describe a cost-utility analysis of an eHealth intervention in patients with ACS	Outpatient eHealth follow-up was likely to be cost-effective vs. usual follow-up	

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Table 1 *Continued*

First author (year)	Clinical trial registration number (study abbreviation)	Country of enrolment	Age, years [mean ± SD or median (IQR)]	Screened sample	Randomized sample	Women, %	Population characteristics	Digital health technologies (digital biomarkers)	Sensor technology	Objective	Results	Comments
Masterson Creber (2022)[30]	NCT02731326 (iHEART)	USA	62 (26–87)[g]	NR	105	25	AF and at least one AF-related risk factor with direct cardioversion or radiofrequency ablation	**KardiaMobile (single-lead)** (cardiac rhythm; arrhythmia detection; HR)	ECG	Categorise AliveCor use as infrequent (≤5 times/week), moderate (>5 to ≤11 times/week) or frequent (>11 times/week)	More frequent KardiaMobile use was associated with AF symptoms and possibly symptomatic cardiac events	
Liu (2022)[31]	NCT04652648	USA	Intervention 49.6 (22–78)[g]; Control 42.9 (29–84)[g]	483	51	Intervention 53; Control 74	Hospitalized patients with positive COVID-19 nasal PCR tests	**KardiaMobile (6-lead)** (cardiac rhythm; arrhythmia detection; HR)	ECG	Assess ECG evidence of cardiotoxicity in the hydroxychloroquine group vs. the observation group	Remote monitoring of 407 ECGs showed no corrected QT interval prolongation or other ECG changes in either group	Daily remote 6-lead ECG monitoring to exclude cardiac toxicity was feasible and operationalized
Lin (2022)[32]	NCT05366803 (WHISH STAR)[a]	USA	78.8 ± 4.3	4791	1257	100	Postmenopausal women with 5-year predicted risk of incident AF ≥ 5% by CHARGE-AF score	**Single-lead ECG patch** (cardiac rhythm; arrhythmia detection; HR)	ECG	Determine the frequency of AF detected by serial 7-day ECG patch screening in older women at elevated AF risk	AF detection increased from 2.5% at baseline to 3.7% at 6 months and 4.9% at 12 months; yield was higher with CHARGE-AF ≥10% (4.2%, 5.9% and 7.2%, respectively)	Most participants with patch-detected AF had no clinical AF diagnosis (36/46; 78%)
De Graaf (2022)[33]	NCT01691586 (REMOTE-CIED)[c]	Multinational (Netherlands, Germany, France, Spain, Switzerland)	Netherlands: RM 67 [60–72], in-clinic 66 [59–72]; Germany RM 66 [58–77], in-clinic 67 [59–74]; RM 66 [58–73], in-clinic 64 [59–73]	≈ 900	600	Netherlands: RM 25.5, in-clinic 24.2; Germany RM 19.7, in-clinic 13.4; RM 18, in-clinic 6.5	HFrEF with first-time ICD and NYHA II-III	**LATITUDE™ platform** (cardiac rhythm; device diagnostics); **weight scale** (body weight); **BP monitor** (BP)	ECG (LATITUDE™ platform); NR (weight scale; BP monitor)	Assess the impact of RM in HF patients with an ICD on medical resource use, direct medical costs, quality-adjusted life-years and travel time	RM reduced medical resource use and travel time; whether it is cost-saving or cost-effective depends strongly on RM costs	
Chiu (2022)[34]	NCT01691586 (REMOTE-CIED)[c]	Multinational (Netherlands, Germany, France, Spain, Switzerland)	65 [59–73]	≈ 900	600	21	HFrEF with first-time ICD and NYHA II-III	**LATITUDE™ platform** (cardiac rhythm; device diagnostics); **weight scale** (body weight); **BP monitor** (BP)	ECG (LATITUDE™ platform); NR (weight scale; BP monitor)	Evaluate the effect of partially substituting in-clinic visits with RM on clinical outcomes in ICD patients	RM was non-inferior to conventional in-clinic visits for clinical outcomes and reduced unnecessary visits without compromising safety or efficiency	
Asch (2022)[35]	NCT02708654 (EMPOWER)	USA	64.5 ± 11.8	8759	566	47.5	HFpEF or HFrEF with a previous hospitalized episode	**Weight scale** (body weight)	NR	Evaluate time to death or all-cause readmission within 12 months	No reduction in the combined endpoint of readmission or mortality in a 12-month intensive RM programme	Financial incentives were provided for completing the measurements

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Varma (2021)[36]	NCT00531661 (CHAMPION)	USA	Intervention 64 ± 13; Control 63.7 ± 11.6	NR	190	Intervention 13; Control 11	NYHA III, CRT recipients and at least 1 HF hospitalization in the prior 12 months	**CardioMEMS™** (PA pressure)	MEMS	Assess the impact of PA pressure-guided medical therapy in CRT recipients	Remote haemodynamic-guided adjustment of medical therapy reduced PA pressure and HF symptoms beyond the effect of CRT	
Szalewska (2021)[37]	NCT02523560 (TELEREH-HF)[b]	Poland	Ischaemic: Intervention 65.5 ± 8.6; Control 64.1 ± 8.8. Non-ischaemic: Intervention 57.0 ± 12.4; Control 58.5 ± 11.6	2333	850	Ischaemic: Intervention 7.1; Control 8. Non-ischaemic: Intervention 19.4; Control 17.9	HFrEF with NYHA I-III after a cardiovascular hospitalization within the 6 months before randomization	**EHO mini device-ECG** (cardiac rhythm; HR); **BP monitor** (BP); **weight scale** (body weight)	ECG; NR (BP monitor; weight scale)	Assess whether HF aetiology affects HCTR outcomes based on functional and clinical parameters	HCTR did not increase days alive and out of hospital in either ischaemic or non-ischaemic aetiology	
Leppert (2021)[38]	NCT02888028	Germany	Intervention 61.5 ± 14.2; Control 63.0 ± 15.3	321	180	Intervention 80.2; Control 84	New implantation or replacement of an ICD	**RM platforms (CareLink; Home Monitoring; Merlin)** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate the effect of RM, in addition to standard of care, on patient-reported outcomes in a mixed ICD cohort	Patient-reported outcomes were not improved by RM in addition to standard-of-care follow-up	
Dorsch (2021)[39]	NCT03149510	USA	Intervention 60.2 ± 9.2; Control 62 ± 9.2	342	83	Intervention 33; Control 37	LVEF of ≤ 40% or >40% (with a left atrial size of >40 mm, brain natriuretic peptide of >200 pg/mL, or N-terminal pro–B-type natriuretic peptide of >800 pg/mL), and recent decompensated HF	**Fitbit Aria/Aria 2** (body weight)	Strain-gauge load cell	Assess the effect of a mobile app self-management intervention on quality of life and HF readmissions	The intervention improved MLHFQ at 6 weeks but effects were not sustained at 12 weeks; no effect on self-reported HF self-management	Fitbit Charge 2 (wrist-worn physical activity monitor) was provided but not used for self-monitoring
Chen (2021)[40]	ACTRN12614000916640 (ITEC-CHF)[d]	Australia	69.8 ± 12.4	NR	67	27	HFrEF	**FORA TN'G W550** (body weight)	Strain-gauge load cell	Evaluate patient feedback following participation in the ITEC-CHF study	The telemonitoring programme was rated highly for usability and was well accepted as part of routine self-management	
Brouwers (2021)[41]	NL5001 (SmartCare-CAD)	Netherlands	60.7 ± 9.5	300	300	11.3	Stable coronary artery disease, acute coronary syndrome and patients who had received coronary revascularization	**Mio Alpha** (HR); **ActiGraph wGT3x-BT** (physical activity)	PPG (Mio Alpha); accelerometer (ActiGraph wGT3x-BT)	Assess the cost-effectiveness of cardiac telerehabilitation with relapse prevention	Cardiac telerehabilitation with relapse prevention was likely to be cost-effective	

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Zakeri (2020)[42]	UKCRN 10383 (REM-HF)	UK	No AF 68.9 ± 10.3, Paroxysmal AF 69 ± 9.8, Persistent/ permanent AF 72.1 ± 9.1	NR	1561	No AF 85 Paroxysmal AF 83.7 Persistent/ permanent AF 90.7	Stable HF with HFrEF, NYHA II–IV and a CIED implanted at least 6 months	**RM platform** (cardiac rhythm; device diagnostics; HR)	ECG	Compare RM vs. usual care on clinical outcomes in patients with and without AF	vs. centre-based cardiac rehabilitation RM increased clinical activity in AF without reducing mortality and was associated with higher cardiovascular hospitalization in persistent/ permanent AF	
Watanabe (2020)[43]	NCT01523704	Japan	77 ± 10	1327	1274	50.4	Single- or dual-chamber pacemaker	**CardioMessenger™** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate the safety and resource use of exclusive RM in pacemaker patients over 2 years	Exclusive remote follow-up over 2 years in pacemaker recipients did not increase major cardiovascular events and reduced resource use	
Tajstra (2020)[44]	NCT02409225 (RESULT)	Poland	Intervention 64 ± 13; Control 64 ± 12	918	600	19	Stable HFrEF with NYHA II–IV and *de novo* implant of ICD/ CRT-D	**RM platforms (CareLink; Home Monitoring; Merlin; LATITUDE)** (cardiac rhythm; device diagnostics; HR)	ECG	Analyse the effect of RM on clinical outcomes in HF patients with ICD/ CRT-D in real-world conditions	RM in HF patients with ICD/CRT-D reduced hospitalization rates in the RM arm	
Piotrowicz (2020)[45]	NCT02523560 (TELEREH-HF)[b]	Poland	Intervention 62.6 ± 10.8; Control 62.2 ± 10.2	2333	850	Intervention 88.7; Control 88.5	HFrEF with NYHA I-III after a cardiovascular hospitalization within the 6 months before randomization	**EHO mini device-ECG** (cardiac rhythm; HR); **BP monitor** (BP); **weight scale** (body weight)	ECG; NR (BP monitor; weight scale)	Assess whether a 9-week HCTR intervention improves clinical outcomes over 12–24 months	HCTR did not increase days alive and out of hospital and did not reduce mortality or hospitalization	
Miyoshi (2020)[46]	UMIN000003351 (MOMOTARO II)	Japan	69.3 ± 10.3	156	57	26.3	ICD/CRT-D, LVEF < 40% or a history of HF hospitalization within the past year	**OptiVol™** (thoracic impedance)	Impedance-based sensing	Examine which lifestyle modifications or medications improve HF indicators in asymptomatic HF patients identified via thoracic impedance	Compared with lifestyle modification, 1-week diuretic and nitrate therapy may be more effective management for HF detected by reduced thoracic impedance	
Lopez-Villegas (2020)[47]	NCT02237404 (NORDLAND)[e]	Norway	75 ± 12	76	50	48	Single or dual-chamber pacemaker	**CardioMessenger™** (cardiac rhythm; device diagnostics; HR)	ECG	Perform an economic assessment of whether telemonitoring pacemakers is a cost-effective alternative	Cost–utility was inconclusive owing to wide CIs; incremental cost-effectiveness ratio/incremental net benefit ranged from	

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											savings to high cost per quality-adjusted life-year, with most incremental cost-effectiveness ratios above Norwegian healthcare system thresholds	
Ding (2020)[48]	ACTRN12614000916640 (ITEC-CHF)[d]	Australia	Intervention 69.5 ± 12.3; Control 70.8 ± 12.4	6587	184	Intervention 27; Control 19	HFrEF	**FORA TN'G W550** (body weight)	Strain-gauge load cell	Evaluate patient adherence to self-management recommendations in an innovative telemonitoring care programme	ITEC-CHF improved adherence to weight monitoring, although withdrawal rates were high	
Versteeg (2019)[49]	NCT01691586 (REMOTE-CIED)[c]	Multinational (Netherlands, Germany, France, Spain, Switzerland)	65 [59–73]	≈ 900	600	21	HFrEF with first-time ICD and NYHA II-III	**LATITUDE™ platform** (cardiac rhythm; device diagnostics); **weight scale** (body weight); **BP monitor** (BP)	ECG (LATITUDE™ platform); NR (weight scale; BP monitor)	Evaluate the effect of RM on patient-reported outcomes during the first 2 years after ICD implantation	RM safely replaced most in-clinic ICD follow-ups; patient-reported health status and ICD acceptance did not differ between RM and in-clinic follow-up	
Pluymaekers (2019)[50]	NCT02248753 (RACE 7 ACWAS)	Netherlands	65 ± 11	3706	437	40	< 36 h haemodynamically stable and symptomatic atrial fibrillation	**MyDiagnostick** (cardiac rhythm; AF detection)	ECG	Determine the presence of sinus rhythm at 4 weeks	A wait-and-see strategy was non-inferior to early cardioversion for return to sinus rhythm at 4 weeks	
López-Liria (2019)[51]	NCT02237404 (NORDLAND)[e]	Norway	75 ± 12	76	50	48	Single or dual-chamber pacemaker	**CardioMessenger™** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate clinical parameters and quality of life at 12-month follow-up in a random sample of pacemaker users of a telemonitoring system	Telemonitoring was as effective as conventional hospital follow-up, with similar outcomes for clinic/emergency department visits and unplanned re-hospitalizations	
Husser (2019)[52]	NCT00538356 (IN-TIME)[f]	Multinational (Australia, Austria, Czech Republic, Denmark, Germany, Israel, Latvia)	65.5 ± 9.4	716	664	19	HFrEF with NYHA II-III, no permanent AF and an indication for dual-chamber ICD/CRT-D	**Home Monitoring™** (cardiac rhythm; device diagnostics; HR)	ECG	Analyse information flow and workflow in IN-TIME and whether differences in message content, speed, completeness and workflow may contribute to heterogeneous results	Limited evidence from other workflow studies suggests that early review after clinical events may be less effective than in IN-TIME	

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Geller (2019)[53]	NCT00538356 (IN-TIME)[f]	Multinational (Australia, Austria, Czech Republic, Denmark, Germany, Israel, Latvia)	65.5 ± 9.4	716	664	19	HFrEF with NYHA II-III, no permanent AF and an indication for dual-chamber ICD/CRT-D	**Home Monitoring™** (cardiac rhythm; device diagnostics; HR)	ECG	Compare IN-TIME outcomes in ICD vs. CRT-D subgroups	Daily telemonitoring may reduce clinical endpoints in HF in both ICD and CRT-D subgroups; absolute benefit appeared greater in higher-risk populations with worse prognosis	
García-Fernández (2019)[54]	(RM-ALONE)	Spain	Intervention 68.9 ± 13.3; Control 68.8 ± 12.8	NR	445	31.1	CIED equipped with Home Monitoring	**Home Monitoring™** (cardiac rhythm; device diagnostics; HR)	ECG	Evaluate the safety and efficiency of a simplified CIED RM protocol in pacemaker and ICD recipients with at least 24-month follow-up	Six-monthly RM was safe and efficient, reducing hospital visits and staff workload	

a–f Superscripts indicate multiple reports from the same trial: WHISH STAR[a]; TELEREH-HF[b]; REMOTE-CIED[c]; ITEC-CHF[d]; NORDLAND[e]; IN-TIME[f].

[g]Reported as median (range), not median [IQR].

[h]Single-arm, non-randomized trial (enrolled $n = 30$).

Abbreviations: ACS, acute coronary syndrome; AF, atrial fibrillation; BP, blood pressure; bpm, beats per minute; CHA_2DS_2-VASc, congestive heart failure, hypertension, age ≥75 years, diabetes mellitus, prior stroke/transient ischaemic attack, vascular disease, age 65–74 years, sex category (female); $CHADS_2$, congestive heart failure, hypertension, age ≥75 years, diabetes mellitus, prior stroke/transient ischaemic attack; CI, confidence interval; CIED, cardiac implantable electronic devices; CRT, cardiac resynchronization therapy; CRT-D, cardiac resynchronization therapy with defibrillator; CRT-P, cardiac resynchronization therapy with pacemaker; ECG, electrocardiogram; HCTR, hybrid comprehensive telerehabilitation; HF, heart failure; HFpEF, heart failure with preserved ejection fraction; HFrEF, heart failure with reduced ejection fraction; HR, heart rate; ICD, implantable cardioverter-defibrillator; ICM, implantable cardiac monitor; IQR, interquartile range; KCCQ-OSS, Kansas City Cardiomyopathy Questionnaire Overall Summary Score; LVEF, left ventricular ejection fraction; MEMS, microelectromechanical systems; MLHFQ, Minnesota Living with Heart Failure Questionnaire; NR, not reported; NT-proBNP, N-terminal pro-B-type natriuretic peptide; NYHA, New York Heart Association; PA, pulmonary artery; PPG, photoplethysmography; RM, remote monitoring; SD, standard deviation.

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physical activity monitors/actigraphs (4), BP monitors (5), CardioMEMS™ (1), LAP monitors (1), and sleep sensors (1).

The DBs measured across the CTs included measurements from ECG [including cardiac rhythm and arrhythmia-related metrics and heart rate (HR)], BP, body weight, bioimpedance/thoracic impedance, PA pressure monitoring, LAP, step counts/physical activity and sleep-related metrics. The sensor technologies used to capture these DBs included ECG, photoplethysmography (PPG), ballistocardiography, impedance-based sensing, oscillometry, microelectromechanical systems (MEMS), strain-gauge load cells, piezoelectric sensors, accelerometers, and altimeters. Among reported sensor technologies, ECG-based sensing was the most common (21/41, 51.2%), whereas among reported DB variables, HR was the most frequently captured (25/50, 50%). Several devices incorporated multiple sensing modalities. For a small number of devices, model-level specifications were not reported.

Methodological quality was good overall (modal modified Jadad score, 5; range, 3–7). Two trials scored 3 on the modified Jadad scale due to their design as single-arm studies and the lack of randomization; however, they were included because they were relevant for evaluating the performance and safety of the V-LAP™ and LUX-Dx™ ICMs. Most of the CTs were unblinded due to the nature of the interventions. Only two studies were double-blind, while three were single-blind. Withdrawals/dropouts, eligibility criteria and statistical analysis were appropriately described in all trials.

Discussion

The use of DBs has increased exponentially in the past decade, accelerated by the COVID-19 pandemic and the need to expand access to broader and effective healthcare. Because DBs can be derived from multiple signals and devices, CTs in cardiovascular medicine are highly heterogeneous with differences in study design and endpoints.

Heart failure

HF is the most common target condition with DBs primarily used for remote monitoring and telemanagement. Overall, evidence is mixed across studies,[26,33,35,42,44,45,53] but it suggests that selected interventions may reduce HF hospitalizations and improve outcomes,[26,44,53] with cost-effectiveness depending on implementation and programme costs.[33] In the included trials, DBs ranged from non-invasive monitoring (e.g. weight, blood pressure, ECG/heart rate and activity) to implantable systems, including device telemetry and haemodynamic sensors (pulmonary artery and left atrial pressure), as summarized in *Table 1*. Importantly, programmes differed in monitoring intensity and in how alerts were handled in practice (who reviewed the data, how often reviews occurred and whether alerts resulted in timely clinical decisions), which likely contributed to heterogeneous results. Through longitudinal assessment outside the clinic, DBs can support earlier identification of clinical deterioration and more timely treatment adjustments than traditional episodic visits, helping refine disease phenotyping and deliver more personalized care (see Central illustration).

Cardiovascular imaging

Imaging increasingly uses AI for image acquisition, quantitative measurement (including segmentation), and post-processing. Nevertheless, most evidence to date is based on agreement with conventional measurements or prediction of clinical events, whereas prospective trials remain limited.

In echocardiography, automation spans both software that helps reduce operator dependence and variability and device innovation, with a wearable prototype being developed for continuous left ventricular ejection fraction (LVEF) monitoring.[55] Convolutional neural networks have enabled autonomous cardiac segmentation and measurement,[56] with automatic annotation of two-dimensional and Doppler acquisitions.[57] A CT demonstrated that the quantification of LVEF by AI was non-inferior to assessment by sonographers,[58] and another trial tested an intelligent Doppler spectrum analysis software designed to estimate LAP using the equation method.[59]

For cardiac magnetic resonance (CMR), trials have focused on benchmarking automated DB measurements against manual method, improving reproducibility and reducing post-processing burden. Among patients after acute MI, an AI-based automated strain analysis showed good concordance with manual analysis, and the automatically derived global longitudinal strain was the only independent predictor of 12-month MACE.[60] For ventricular arrhythmia substrates, CMR improves risk stratification through a DL contrast-free virtual native enhancement showing high agreement with late gadolinium enhancement (LGE)-CMR for myocardial scar quantification.[61] CMR further extends into ventricular tachycardia management, the VOYAGE trial evaluated AI automation software to integrate LGE-CMR with electroanatomical mapping for ventricular tachycardia ablation.[62]

In coronary computed tomography angiography (CCTA), DBs include automated coronary artery calcium scoring, quantitative plaque burden and compositional phenotyping and perivascular/adipose tissue signatures used for risk prediction.[63–66] Functional assessment can also be derived via fractional flow reserve-computed tomography (FFR-CT), with ML-derived FFR-CT showing equivalent diagnostic performance to computational fluid dynamics–based FFR-CT.[67] In this context, CCTA studies have reported prognostic associations, including AI-derived plaque volume and stenosis quantification are prognostic for incident MI,[63] and ML risk models improve 5-year mortality prediction beyond established clinical scores.[68] Similarly, in invasive imaging, deep-learning (DL) algorithms have been applied to coronary angiography to localize and grade stenoses,[69,70] identify plaque erosion,[71] and detect reduced LVEF.[72]

Cardiac electrophysiology and rhythm monitoring

In cardiac electrophysiology, DBs are mainly focused on rhythm monitoring and detection of cardiac arrhythmias using different technologies for recording. Different trials implemented single-lead ECG[73] and PPG[74,75] for atrial fibrillation (AF) screening, and have also evaluated post–acute coronary syndrome (ACS) monitoring with ICMs and portable ECG devices showing that such monitoring may be beneficial in selected high-risk groups [e.g. elevated CHA_2DS_2-VASc or Global Registry of Acute Coronary Events scores]. In these post-ACS trials, enhanced monitoring increased detection of incident AF as well as pauses/high-grade atrioventricular block and ventricular tachyarrhythmias, mainly prompting anticoagulation initiation and, when indicated, antiarrhythmic therapy or device implantation.[16,76,77]

Beyond simple ECG and PPG tracings, these DBs can represent a basis for predictive analyses using AI. Most evidence to date relates to retrospective development and validation, including prediction of future AF from single-lead ECG strips recorded in sinus rhythm[78] and standard 12-lead ECG.[79] AI models have also been used to detect hyperkalaemia from a

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2- or 4-lead ECG[80] and to identify hypertrophic cardiomyopathy from a 12-lead ECG.[81] ML models have also been developed to predict atrial tachyarrhythmia recurrence after AF catheter ablation.[82]

Prospective evidence demonstrating clinical impact remains more limited. For sudden cardiac death risk stratification, improvements will likely require integrating multiple DBs across modalities rather than relying on single-signal models.[83] In this context, digital twins—computational representations that integrate multimodal patient data—are novel tools to support personalized arrhythmia risk stratification and therapy planning.[84] Early evidence suggests that ML can be applied to diverse ECG-derived DBs. Examples include models based on heartbeat intervals, which have shown high precision for predicting life-threatening ventricular arrhythmias,[85] QRS complex shape used to predict ventricular fibrillation.[86] In patients with ICD/CRT-D devices, daily remote-monitoring data have also been used in machine-learning models to predict impending appropriate device therapies, including ICD shocks.[23,87]

Acute and intensive cardiovascular care

DBs captured by DHTs are increasingly incorporated into risk stratification scores and used to continuously monitor patients with high-risk acute cardiovascular conditions.[88] DBs may improve triage, diagnosis and outcomes in patients with acute CVD through earlier identification of myocardial injury and coronary occlusion before hospital arrival.[89] For instance, a wrist-worn transdermal infrared sensor predicted elevated cardiac troponins and was associated with regional wall motion abnormalities and significant coronary stenosis,[90] while three-lead ambulatory occlusion detection systems have been validated[91] and AI models applied to 12-lead ECGs outperformed ST-segment elevation myocardial infarction criteria in identifying acute coronary occlusion MI.[92]

In hospitalized patients, ML early warning models using routinely measured vital signs can outperform aggregate scores on many outcomes, although performance decreases as the prediction window lengthens.[93] Notably, ML-based phenotyping in cardiogenic shock identified a high-risk cardiometabolic subgroup with the greatest likelihood of progression to Society for Cardiovascular Angiography and Interventions shock (SCAI) stages D/E and in-hospital mortality.[94] Prospective outcome data are limited but an AI ECG alert for reduced LVEF is among the few trials suggesting that a DB can improve survival. The alert prompted earlier clinical review and was associated with lower 90-day mortality.[19]

In the most time-critical scenario, out-of-hospital cardiac arrest (OHCA) is a major application with reported improvements in ECG classification, early dispatch and prognostication after return of spontaneous circulation.[95] AI algorithms have been investigated to strengthen prediction, detection, and management, including resource allocation and cardiopulmonary resuscitation quality and success.[96,97] Using ECG, ML algorithms were effective in predicting cardiac arrest within 24 h,[98] differentiating pulseless electrical activity-OHCA from ventricular fibrillation-OHCA[99] and identifying OHCA with acute coronary occlusion.[100] ML has also been embedded into automated external defibrillators,[101] optimizing shock/no-shock decisions during rhythm analysis[102] without interrupting chest compressions.[103] Beyond algorithms, novel DHTs are emerging in this field. In the Jewel IDE study, a water-resistant patch wearable cardioverter-defibrillator was shown to be safe and effective, with a high number of successful defibrillations and few adverse events.[104]

Prevention and cardiac rehabilitation

In primary prevention, DBs have enormous potential for early identification of individuals at risk of CVD before symptoms manifest. Derived from data collected through wearables, smartphones, and other DHTs, DBs offer continuous monitoring of parameters such as cardiac rhythm, HR variability, BP, physical activity, and sleep patterns. For instance, smartphone PPG screening identified more than twice as many cases of AF at an early stage compared with usual care.[74] Activity trackers can provide DB derived feedback and boost physical activity across various age groups and populations.[105] Additional applications include monitoring CVD risk factors like BP via cuffless sensors,[106,107] and assessing psychological stress or sleep quality through HR variability.[108–110] Sports cardiology is currently exploring the potential of wearable devices and AI for monitoring, risk prediction and shared decision-making in athletes with structural or electrical heart diseases. While this field shows promise, there is a lack of evidence supporting its effectiveness and important ethical and legal issues remain to be addressed.[111]

Comprehensive cardiac rehabilitation (CR) is recommended for structured secondary CVD prevention.[112] Digitally enhanced home-based programmes (cardiac telerehabilitation) are viable alternatives to centre-based programmes and may enable more personalized delivery, with improved participation and adherence.[113,114] Biosensing wearables and mobile devices enable the remote delivery of core components of CR, including exercise training and activity monitoring, nutritional counselling, and risk factor management, while capturing DBs that largely mirror those used in primary prevention.[113] Systematic reviews suggest modest benefits of mHealth on exercise capacity, physical activity, BP, and body weight, but evidence quality is moderate and interventions are heterogeneous.[115] Early evidence indicates that selected DBs, such as daily step count and BP, can provide actionable biofeedback to guide goal directed therapy.[116,117] Nevertheless, major challenges in rehabilitation include usability of DHTs in older and multimorbid CVD populations, defining optimal analysis for DBs, and reaching agreement on meaningful outcomes.[118]

Development and validation of digital biomarkers: methodological considerations

DHTs that collect DBs rely on hardware, software, and analytic pipelines that must be developed, validated and, when applicable, certified in accordance with regulatory requirements. For systems that incorporate self-measurement, the reliability of data acquisition, transmission, storage, and processing is critical.[119] Validating DBs for clinical practice and for use as surrogate endpoints in research requires selecting appropriate digital instruments. Factors to consider when validating novel digital endpoints in CTs include endpoint selection, technical validation, clinical validation, and candidate endpoint evaluation.[120–122] In technical validation, the new assessment is compared with a gold standard under controlled conditions to demonstrate internal validity for the target construct and minimize bias and confounding.[120,123] Clinical validation assesses accuracy, safety and clinical utility in the intended setting. Two issues are particularly relevant at this stage: results may not generalize beyond the study cohort because measurement accuracy can vary across populations (e.g. PPG measurements in elderly individuals), and differences in disease prevalence can affect predictive values. Accordingly, validation should consider populations often underrepresented in CTs (e.g. ethnic minorities, people

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with advanced chronic conditions, sex/gender differences, and learning difficulties) and be complemented by real-world evaluations.[124]

Even after technical and clinical validation, biomarkers should not be assumed to function as surrogate endpoints.[125] AI has the potential to assist in the identification of 'omics' biomarkers,[126] and, by extension, may also be applicable to the development of DBs. Wearable technologies generate longitudinal, multi-signal data that ML methods can use to derive candidate DBs.[127] This is relevant for behavioural interventions, as behaviour reflects complex interactions among biological, environmental, and social determinants that are difficult to quantify[128] but also for routinely collected hospital data, where ML methods can generate algorithm-based DBs that predict clinically relevant outcomes.[129]

Barriers to the implementation of digital biomarkers in cardiovascular care

Patients with CVD often require frequent monitoring as well as intensive and precise longitudinal management. The use of DHTs—DBs in particular—is highly desirable, but implementation in routine clinical practice remains challenging, as highlighted in the European Society of Cardiology (ESC) Working Group on e-Cardiology position paper on the use of commercially available wearable technology for heart rate and activity tracking in primary and secondary cardiovascular prevention.[130] This is exemplified by the lower uptake of wearables among individuals with established CVD compared with those at risk for CVD and the general population[131] and by the variability across ESC member countries in the implementation of remote monitoring of CIEDs.[132] Despite the widespread availability of electronic devices in many regions of the world, the utilization of DBs for patient management is not without difficulty for a variety of reasons:

- Interoperability and electronic medical records (EMRs): EMRs provide the clinical context needed to interpret DB signals, including clinical notes, laboratory tests, ECGs, echocardiography and other imaging modalities. However, a key gap is the limited ability to integrate DB data into EMRs. This separation restricts access to the clinical variables and outcomes needed to develop and validate DBs. At the same time, maintaining this separation may improve security by limiting unnecessary data aggregation.[133,134] Potential solutions include standardized data formats and improved interoperability frameworks to enable secure and permissioned data exchange.
- Regulatory barriers: Validation and post-market performance monitoring remain insufficiently standardized across many DHTs, particularly consumer-grade tools, contributing to within- and between-device measurement variability and hampering the development of novel DBs.[135,136] In parallel, Europe and the US have outlined the criteria for classifying clinical decision support software as software as a medical device, which can increase evidence requirements, raise development costs and slow the deployment of new tools.[137]
- Privacy and security: Individual, personal health-related information on digital platforms is highly sensitive. Beyond data protection, DBs raise governance risks related to data ownership and secondary use, as large technology platforms increasingly mediate the collection, storage, and sharing of personal health data. Due to genuine concerns about these issues, patients may decide not to take part in therapeutic schemes involving digital technologies. Safeguards are in place to protect patient data and to reduce the risk of data leaks, hacking or breaches, but further efforts are necessary to fully reassure the public that personal data are truly anonymized and protected. Laws and regulations exist in Europe and the US that provide a reasonable degree of data protection, but additional regional and local regulatory tools are needed to further reassure patients. In this context, providing patients with clear information about their data rights could enhance confidence in the use of DBs in the near future.
- Training: Healthcare professionals as well as patients and their carers must be educated regarding the application and implementation of DHTs, as these often differ markedly from conventional models.[119]
- Affordability and equity: Efforts should focus on making consumer electronics more affordable and establishing effective reimbursement policies. A key unresolved issue is who will bear these costs (patients, insurers, healthcare systems, or government agencies), including not only the device itself but also data infrastructure and clinician time required to review and act on DBs.[12,13] The ESC-European Heart Rhythm Association (EHRA) Atlas reports marked cross-country disparities in access to guideline-recommended arrhythmia care and identifies dissatisfaction with national reimbursement systems as a recurrent barrier to implementation.[132] Moreover, research that is vital for the implementation of DHTs in cardiovascular care has often failed to include ethnic minority populations, culturally diverse individuals and socioeconomically disadvantaged groups, undermining equity in access to DHTs.
- Digital literacy: Even in high-income countries, there is a clear 'digital divide' between people who have access to DHTs and possess the digital literacy necessary to use these technologies, and those who do not. Many people have low levels of technology literacy, i.e. older patients and people with disabilities, which may limit their ability to use smartphones and digital therapeutic apps effectively. Interestingly, however, data from the Strategy of Blood Pressure Intervention in the Elderly Hypertensive Patients study showed that most older patients enrolled were able to use the smartphone app to submit blood pressure readings.[138]
- Motivation: Lack of motivation, limited awareness of or trust in medical strategies such as telemedicine, or resistance to adopting new treatment paradigms, are also barriers to the implementation of these useful methodologies for patients as well as physicians.[119] Additionally, lack of patient engagement decreases the accuracy of measurements.
- Outcome evidence: DBs have been correlated with multiple clinical markers and secondary endpoints. However, their impact on hard clinical outcomes (e.g. mortality) is uncertain, and evidence for effects on healthcare utilization (e.g. hospitalizations and visits) is also limited. This remains a promising area for future outcome-driven trials.
- Cost-effectiveness evidence: Given rising costs and demand on health systems, cost-effectiveness evidence is increasingly important. Recent studies suggest that DHTs—particularly software designed to support lifestyle change—may enable cost-effective delivery of interventions at scale.[139] However, health-economic evidence for DBs remains relatively scarce and heterogeneous.[33,140,141]

Future perspectives

In the coming years, DHTs are expected to dominate biomarker capture across the cardiovascular spectrum—from the general population to high-risk individuals and patients with established CVD. DBs will further extend beyond traditional care settings,

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allowing remote and near-continuous monitoring outside the clinic, occasionally supported by AI methods.[142] DBs will also help evaluate treatment response, facilitate guideline implementation, and promote patient engagement.

A major underused opportunity lies in clinical research, particularly the integration of DBs as surrogate endpoints. The Clinical Trials Transformation Initiative has issued recommendations on incorporating DHT-derived endpoints, including DBs, within clinical outcome assessments.[143] This could allow earlier and more precise ascertainment of outcomes, while also supporting novel endpoints that are not feasible with episodic monitoring. By providing objective measures that reduce bias and random error, DBs complement patient- and clinician-reported outcomes and may improve endpoint specificity, particularly when the signal-to-noise ratio is high.[144]

Several emerging DB modalities have been explored as proof-of-concept and require rigorous evaluation in adequately powered, late-phase CTs. For example, facial imaging and ocular photographs have been explored for hypertension screening, while voice features have been investigated as potential DBs of AF and CAD.[145–148] To translate these innovations into routine clinical practice, regulatory frameworks must be supported by robust validation standards and clear requirements for data privacy and governance. Addressing these challenges will be essential for their widespread adoption. Ultimately, digital health and DBs are likely to support a shift towards proactive 4P care (preventive, participatory, predictive and personalized) through clinician–patient collaboration.

Conclusions

Compared with traditional biomarkers, DBs facilitate care along the continuum from prevention and prediction to diagnosis, treatment monitoring and prognostication. By capturing real-world data through DHTs, DBs can reduce reliance on episodic clinic visits and support earlier detection of clinical deterioration and more timely treatment adjustment. Selected DBs have demonstrated clinical utility in specific cardiovascular conditions, although current trials remain heterogeneous in technologies and endpoints. To support broader adoption in routine care, robust validation, clear regulatory requirements covering data privacy and governance, interoperability with clinical systems, and stronger evidence on clinical outcomes and cost-effectiveness will be needed. Finally, continuous innovation in AI technologies is likely to amplify the impact of DHTs in both research and clinical practice, supporting patient self-management and improving day-to-day health.

Supplementary material

Supplementary material is available at *European Heart Journal – Digital Health*.

Author contributions

Pablo M. Corredoira [Conceptualization, Writing—original draft, Writing—review & editing (equal)], David Duncker [Conceptualization (supporting)], Marcus Dörr [Conceptualization (supporting)], Matthias Wilhelm [Conceptualization (supporting)], Marco Tubaro [Conceptualization (supporting)], Mark Schuuring [Conceptualization (supporting)], Mamas Mamas [Conceptualization (supporting)], Steffen E. Petersen [Conceptualization (supporting)], Rafael Vidal-Pérez [Conceptualization (supporting)], Hareld M. C. Kemps [Conceptualization (supporting)], Emanuela T. Locati [Conceptualization (supporting)], Christian Mueller [Conceptualization (supporting)], Magnus T. Jensen [Conceptualization (supporting)], Raffaele De Lucia [Conceptualization (supporting)], Julia Ramírez [Conceptualization (supporting)], Matthijs Cluitmans [Conceptualization (supporting)], Nurgül Keser [Conceptualization (supporting)], Axel Verstrael [Conceptualization (supporting)], Polychronis Dilaveris [Conceptualization (supporting)], Paul A. Friedman [Conceptualization (supporting)], Rubén Casado-Arroyo [Conceptualization, Methodology, Writing—original draft, Writing—review & editing (lead)], Juan Carlos Kaski [Conceptualization (supporting)], and Loreena Hill [Conceptualization (supporting)].

Conflicts of interest: D.D. has received a fellowship grant, modest lecture honoraria, and travel grants/support from Abbott, AstraZeneca, Bayer, Biotronik, Boehringer Ingelheim, Boston Scientific, Bristol Myers Squibb, CVRx, Medtronic, MicroPort, Pfizer, Sanofi, and Zoll. M.J.S. reports being a member of the Dutch CardioVascular Alliance consortium ADMINISTER II, which is supported by public or not-for-profit organizations, including the Hartcentrum Twente Foundation, and by partners making independent contributions to the research institute, including AstraZeneca and Boehringer Ingelheim. M.J.S. has also received grant funding from the Pioneers in Healthcare scheme, University of Twente, and TKI-PPP (Health Holland). S.E.P. reports grants/contracts from UKRI, Barts Charity, the Medical Research Council, the National Institute for Health and Care Research, and the British Heart Foundation; royalties/licence fees from Oxford University Press related to the EACVI CMR textbook; consulting fees from Circle Cardiovascular Imaging, Inc., Canada; honoraria for lectures/presentations at the CMR Academy in Berlin; support for attending meetings and/or travel related to his role as president and immediate past president of the EACVI; and serves as Chair of the Data Safety Monitoring Board for the Proteus Trial. C.M. has received research support from the Swiss National Science Foundation, the Swiss Heart Foundation, University Hospital Basel, the University of Basel, Abbott, AstraZeneca, Beckman Coulter, Idorsia, Novartis, Ortho Diagnostics, Quidel, Roche, Siemens, Singulex, SpinChip, and Sphingotec, with payments made to the institution; and consulting and speaker/lecture honoraria from Amgen, AstraZeneca, Bayer, Boehringer Ingelheim, Bristol Myers Squibb, Idorsia, Novartis, Osler, Roche, Sanofi, and SpinChip, with payments made to the institution. M.C. has a part-time appointment/employment (0.4 FTE) as Senior Scientist at Philips Innovation & Strategy, Philips, Eindhoven, the Netherlands, with payments made to the individual. P.A.F. reports that Mayo Clinic has licensed a number of AI-ECG algorithms to Anumana, Eko Health, and AliveCor, and that Mayo Clinic, P.A.F., and other inventors may benefit financially from the commercialization of these algorithms. R.C.A. has received small educational grants from Boston Scientific and Abbott for educational purposes, with payments made to the institution. All other authors declare no conflicts of interest.

Funding

This work received no specific funding from any public, commercial, or not-for-profit agency.

References

1. Landolina M, Perego GB, Lunati M, Curnis A, Guenzati G, Vicentini A, *et al.* Remote monitoring reduces healthcare use and improves quality of care in heart failure patients with implantable defibrillators: the evolution of management strategies of heart failure patients with implantable defibrillators (EVOLVO) study. *Circulation* 2012;**125**:2985–2992.

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2. Burri H, da Costa A, Quesada A, Ricci RP, Favale S, Clementy N, *et al.* Risk stratification of cardiovascular and heart failure hospitalizations using integrated device diagnostics in patients with a cardiac resynchronization therapy defibrillator. *Europace* 2018;**20**:e69–e77.
3. Biomarker. European Medicines Agency (EMA) [Internet]. [cited 2025 May 2]. https://www.ema.europa.eu/en/glossary-terms/biomarker
4. FDA-NIH Biomarker Working Group. BEST (Biomarkers, EndpointS, and other Tools) Resource [Internet]. Silver Spring (MD): Food and Drug Administration (US); 2016 [cited 2026 Feb 7]. http://www.ncbi.nlm.nih.gov/books/NBK326791/
5. Califf RM. Biomarker definitions and their applications. *Exp Biol Med* 2018;**243**:213–221.
6. European Medicines Agency (EMA). Qualification of novel methodologies for medicine development [Internet]. 2020 [cited 2025 May 2]. https://www.ema.europa.eu/en/qualification-novel-methodologies-medicine-development
7. Vasudevan S, Saha A, Tarver ME, Patel B. Digital biomarkers: convergence of digital health technologies and biomarkers. *NPJ Digit Med* 2022;**5**:36.
8. Macias Alonso AK, Hirt J, Woelfle T, Janiaud P, Hemkens LG. Definitions of digital biomarkers: a systematic mapping of the biomedical literature. *BMJ Health Care Inform* 2024;**31**:e100914.
9. Kim YI, Choi Y, Park J. The role of continuous glucose monitoring in physical activity and nutrition management: perspectives on present and possible uses. *Phys Act Nutr* 2023;**27**:44–51.
10. Inan OT, Tenaerts P, Prindiville SA, Reynolds HR, Dizon DS, Cooper-Arnold K, *et al.* Digitizing clinical trials. *NPJ Digit Med* 2020;**3**:101.
11. Durán CO, Bonam M, Björk E, Hughes R, Ghiorghiu S, Massacesi C, *et al.* Implementation of digital health technology in clinical trials: the 6R framework. *Nat Med* 2023;**29**:2693–2697.
12. Boriani G, Brachmann J, Lewalter T, Wright DJ, Badertscher P, Gale CP, *et al.* Access and reimbursement of ambulatory cardiac monitoring across Europe. *Eur Heart J Digit Health* 2025;**6**:1282–1292.
13. Traykov V, Puererfellner H, Burri H, Foldesi CL, Scherr D, Duncker D, *et al.* EHRA perspective on the digital data revolution in arrhythmia management: insights from the association's annual summit. *Europace* 2025;**27**:euaf149.
14. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, *et al.* The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 2021;**372**:n71.
15. Victoria-Castro AM, Martin ML, Yamamoto Y, Melchinger H, Weinstein J, Nguyen A, *et al.* Impact of Digital Health Technology on Quality of Life in Patients With Heart Failure. *JACC Heart Fail* 2024;**12**:336–348.
16. Jøns C, Bloch Thomsen PE, Riahi S, Smilde T, Bach U, Jacobsen PK, *et al.* Arrhythmia monitoring and outcome after myocardial infarction (BIO\|GUARD-MI): a randomized trial. *Front Cardiovasc Med* 2024;**11**:1300074.
17. Gomez SE, Larson J, Hlatky MA, Rodriguez F, Wheeler M, Greenland P, *et al.* Prevalence of frequent premature ventricular contractions and nonsustained ventricular tachycardia in older women screened for atrial fibrillation in the Women's Health Initiative. *Heart Rhythm* 2024;**21**:1280–1288.
18. Alshahrani NS, Hartley A, Howard J, Hajhosseiny R, Khawaja S, Seligman H, *et al.* Randomized Trial of Remote Assessment of Patients After an Acute Coronary Syndrome. *J Am Coll Cardiol* 2024;**83**:2250–2259.
19. Lin CS, Liu WT, Tsai DJ, Lou YS, Chang CH, Lee CC, *et al.* AI-enabled electrocardiography alert intervention and all-cause mortality: a pragmatic randomized clinical trial. *Nat Med* 2024;**30**:1461–1470.
20. Stolen C, Rosman J, Manyam H, Kwan B, Kelly J, Perschbacher D, *et al.* Preliminary results from the LUX-Dx insertable cardiac monitor remote programming and performance (LUX-Dx PERFORM) study. *Clin Cardiol* 2023;**46**:100–107.
21. Nassif ME, Nguyen D, Spertus JA, Gosch KL, Tang F, Windsor SL, *et al.* Association Between Change in Ambulatory Pulmonary Artery Pressures and Natriuretic Peptides in Patients with Heart Failure: Results From the EMBRACE-HF Trial. *J Card Fail* 2023;**29**:1324–1328.
22. Kronborg MB, Frausing MHJP, Malczynski J, Riahi S, Haarbo J, Holm KF, *et al.* Atrial pacing minimization in sinus node dysfunction and risk of incident atrial fibrillation: a randomized trial. *Eur Heart J* 2023;**44**:4246–4255.
23. Ginder C, Li J, Halperin JL, Akar JG, Martin DT, Chattopadhyay I, *et al.* Predicting malignant ventricular arrhythmias using real-time remote monitoring. *J Am Coll Cardiol* 2023;**81**:949–961.
24. Desai AS, Maisel A, Mehra MR, Zile MR, Ducharme A, Paul S, *et al.* Hemodynamic-Guided Heart Failure Management in Patients With Either Prior HF Hospitalization or Elevated Natriuretic Peptides. *JACC Heart Fail* 2023;**11**:691–698.
25. D'Amario D, Meerkin D, Restivo A, Ince H, Sievert H, Wiese A, *et al.* Safety, Usability, and Performance of a Wireless Left Atrial Pressure Monitoring System in Patients with Heart Failure: The VECTOR-HF Trial. *Eur J Heart Fail* 2023;**25**:902–911.
26. Wita M, Orszulak M, Szydło K, Wróbel W, Filipecki A, Simionescu K, *et al.* The usefulness of telemedicine devices in patients with severe heart failure with an implanted cardiac resynchronization therapy system during two years of observation. *Kardiol Pol* 2022;**80**:41–48.
27. Spindler H, Dyrvig AK, Schacksen CS, Anthonimuthu D, Frost L, Gade JD, *et al.* Increased motivation for and use of digital services in heart failure patients participating in a telerehabilitation program: a randomized controlled trial. *mHealth* 2022;**8**:25.
28. Piotrowicz E, Mierzyńska A, Jaworska I, Opolski G, Banach M, Zaręba W, *et al.* Relationship between physical capacity and depression in heart failure patients undergoing hybrid comprehensive telerehabilitation vs. usual care: subanalysis from the TELEREH-HF Randomized Clinical Trial. *Eur J Cardiovasc Nurs* 2022;**21**:568–577.
29. Treskes RW, van den Akker-van Marle ME, van Winden L, van Keulen N, van der Velde ET, Beeres S, *et al.* The Box—eHealth in the Outpatient Clinic Follow-up of Patients With Acute Myocardial Infarction: Cost-Utility Analysis. *J Med Internet Res* 2022;**24**:e30236.
30. Masterson Creber RM, Reading Turchioe M, Biviano A, Caceres B, Garan H, Goldenthal I, *et al.* Cardiac symptom burden and arrhythmia recurrence drives digital health use: results from the iHEART randomized controlled trial. *Eur J Cardiovasc Nurs* 2022;**21**:107–115.
31. Liu HH, Ezekowitz MD, Columbo M, Khan O, Martin J, Spahr J, *et al.* Testing the feasibility of operationalizing a prospective, randomized trial with remote cardiac safety EKG monitoring during a pandemic. *J Interv Card Electrophysiol* 2022;**63**:345–356.
32. Lin JY, Larson J, Schoenberg J, Sepulveda A, Tinker L, Wheeler M, *et al.* Serial 7-Day Electrocardiogram Patch Screening for AF in High-Risk Older Women by the CHARGE-AF Score. *JACC Clin Electrophysiol* 2022;**8**:1523–1534.
33. de Graaf G, Timmermans I, Meine M, Alings M, Pedersen SS, Mabo P, *et al.* Economic evaluation of remote monitoring of patients with an implantable cardiac defibrillator (REMOTE-CIED study). *J Telemed Telecare* 2024;**30**:1173–1185.
34. Chiu CSL, Timmermans I, Versteeg H, Zitron E, Mabo P, Pedersen SS, *et al.* Effect of remote monitoring on clinical outcomes in European heart failure patients with an implantable cardioverter-defibrillator: secondary results of the REMOTE-CIED randomized trial. *Europace* 2022;**24**:256–267.
35. Asch DA, Troxel AB, Goldberg LR, Tanna MS, Mehta SJ, Norton LA, *et al.* Remote monitoring and behavioral economics in managing heart failure in patients discharged from the hospital: a randomized clinical trial. *JAMA Intern Med* 2022;**182**:643–649.
36. Varma N, Bourge RC, Stevenson LW, Costanzo MR, Shavelle D, Adamson PB, *et al.* Remote Hemodynamic-Guided Therapy of Patients With Recurrent Heart Failure Following Cardiac Resynchronization Therapy. *J Am Heart Assoc* 2021;**10**:e017619.
37. Szalewska D, Główczyńska R, Piotrowicz R, Kowalik I, Pencina MJ, Opolski G, *et al.* An Aetiology-Based Subanalysis of the Telerehabilitation in Heart Failure Patients (TELEREH-HF) Trial. *ESC Heart Fail* 2021;**8**:1263–1273.
38. Leppert F, Siebermair J, Wesemann U, Martens E, Sattler SM, Scholz S, *et al.* The INFluence of Remote monitoring on Anxiety/depRession, quality of lifE, and Device acceptance in ICD patients: a prospective, randomized, controlled, single-center trial. *Clin Res Cardiol* 2021;**110**:789–800.
39. Dorsch MP, Farris KB, Rowell BE, Hummel SL, Koelling TM. The Effects of the ManageHF4Life Mobile App on Patients With Chronic Heart Failure: Randomized Controlled Trial. *JMIR Mhealth Uhealth* 2021;**9**:e26185.
40. Chen SH, Edwards I, Jayasena R, Ding H, Karunanithi M, Dowling A, *et al.* Patient Perspectives on Innovative Telemonitoring Enhanced Care Program for Chronic Heart Failure (ITEC-CHF): Usability Study. *JMIR Cardio* 2021;**5**:e24611.
41. Brouwers RWM, van der Poort EKJ, Kemps HMC, van den Akker-van Marle ME, Kraal JJ. Cost-effectiveness of Cardiac Telerehabilitation With Relapse Prevention for the Treatment of Patients With Coronary Artery Disease in the Netherlands. *JAMA Netw Open* 2021;**4**:e2136652.
42. Zakeri R, Morgan JM, Phillips P, Kitt S, Ng GA, McComb JM, *et al.* Impact of remote monitoring on clinical outcomes for patients with heart failure and atrial fibrillation: results from the REM-HF trial. *Eur J Heart Fail* 2020;**22**:543–553.
43. Watanabe E, Yamazaki F, Goto T, Asai T, Yamamoto T, Hirooka K, *et al.* Remote Management of Pacemaker Patients With Biennial In-Clinic Evaluation. *Circ Arrhythm Electrophysiol* 2020;**13**:e007734.
44. Tajstra M, Sokal A, Gadula-Gacek E, Kurek A, Wozniak A, Niedziela J, *et al.* Remote supervision to decrease hospitalization rate (RESULT) study in patients with implanted cardioverter-defibrillator. *Europace* 2020;**22**:769–776.

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45. Piotrowicz E, Pencina MJ, Opolski G, Zareba W, Banach M, Kowalik I, *et al.* Effects of a 9-week hybrid comprehensive telerehabilitation program on long-term outcomes in patients with heart failure: the telerehabilitation in heart failure patients (TELEREH-HF) randomized clinical trial. *JAMA Cardiol* 2020;**5**:300–308.
46. Miyoshi A, Nishii N, Okamoto Y, Fujita S, Kawamoto K, Okawa K, *et al.* Lifestyle Modification or Medication to Improve Condition of Patients With Asymptomatic Heart Failure: Monitoring and Management of OptiVol Alert to Reduce Heart Failure Hospitalization II (MOMOTARO II) Study. *Circ J* 2020;**84**:456–462.
47. Lopez-Villegas A, Catalan-Matamoros D, Peiro S, Lappegard KT, Lopez-Liria R, Andò G. Cost–utility analysis of telemonitoring versus conventional hospital-based follow-up of patients with pacemakers. *The NORDLAND randomized clinical trial. PLoS One* 2020;**15**:e0226188.
48. Ding H, Jayasena R, Chen SH, Maiorana A, Dowling A, Layland J, *et al.* The Effects of Telemonitoring on Patient Compliance With Self-Management Recommendations and Outcomes of the Innovative Telemonitoring Enhanced Care Program for Chronic Heart Failure: Randomized Controlled Trial. *J Med Internet Res* 2020;**22**:e17559.
49. Versteeg H, Timmermans I, Widdershoven J, Kimman GJ, Prevot S, Rauwolf T, *et al.* Effect of remote monitoring on patient-reported outcomes in European heart failure patients with an implantable cardioverter-defibrillator: primary results of the REMOTE-CIED randomized trial. *Europace* 2019;**21**:1360–1368.
50. Pluymaekers NAHA, Dudink EAMP, Luermans JGLM, Meeder JG, Lenderink T, Widdershoven J, *et al.* Early or Delayed Cardioversion in Recent-Onset Atrial Fibrillation. *N Engl J Med* 2019;**380**:1499–1508.
51. López-Liria R, López-Villegas A, Enebakk T, Thunhaug H, Lappegård KT, Catalán-Matamoros D. Telemonitoring and Quality of Life in Patients after 12 Months Following a Pacemaker Implant: the Nordland Study, a Randomised Trial. *Int J Environ Res Public Health* 2019;**16**:2001.
52. Husser D, Geller JC, Taborsky M, Schomburg R, Bode F, Nielsen JC, *et al.* Remote monitoring and clinical outcomes: details on information flow and workflow in the IN-TIME study. *Eur Heart J Qual Care Clin Outcomes* 2019;**5**:136–144.
53. Geller JC, Lewalter T, Bruun NE, Taborsky M, Bode F, Nielsen JC, *et al.* Implant-based multi-parameter telemonitoring of patients with heart failure and a defibrillator with vs. without cardiac resynchronization therapy option: a subanalysis of the IN-TIME trial. *Clin Res Cardiol* 2019;**108**:1117–1127.
54. García-Fernández FJ, Osca Asensi J, Romero R, Fernández Lozano I, Larrazabal JM, Martínez Ferrer J, *et al.* Safety and efficiency of a common and simplified protocol for pacemaker and defibrillator surveillance based on remote monitoring only: a long-term randomized trial (RM-ALONE). *Eur Heart J* 2019;**40**:1837–1846.
55. Hu H, Huang H, Li M, Gao X, Yin L, Qi R, *et al.* A wearable cardiac ultrasound imager. *Nature* 2023;**613**:667–675.
56. Zhang J, Gajjala S, Agrawal P, Tison GH, Hallock LA, Beussink-Nelson L, *et al.* Fully automated echocardiogram interpretation in clinical practice. *Circulation* 2018;**138**:1623–1635.
57. Tromp J, Seekings PJ, Hung CL, Iversen MB, Frost MJ, Ouwerkerk W, *et al.* Automated interpretation of systolic and diastolic function on the echocardiogram: a multicohort study. *Lancet Digit Health* 2022;**4**:e46–e54.
58. He B, Kwan AC, Cho JH, Yuan N, Pollick C, Shiota T, *et al.* Blinded, randomized trial of sonographer versus AI cardiac function assessment. *Nature* 2023;**616**:520–524.
59. Jin Y, Wen CY, Yue F, Wang H, Yin L, Zhao Y, *et al.* Automatic quantitative measurement of left atrial pressure using mitral regurgitation spectrum: clinical study on comparison with floating catheter. *Eur J Med Res* 2022;**27**:217.
60. Backhaus SJ, Aldehayat H, Kowallick JT, Evertz R, Lange T, Kutty S, *et al.* Artificial intelligence fully automated myocardial strain quantification for risk stratification following acute myocardial infarction. *Sci Rep* 2022;**12**:12220.
61. Zhang Q, Burrage MK, Shanmuganathan M, Gonzales RA, Lukaschuk E, Thomas KE, *et al.* Artificial intelligence for contrast-free MRI: scar assessment in myocardial infarction using deep learning–based virtual native enhancement. *Circulation* 2022;**146**:1492–1503.
62. Lilli A, Parollo M, Mazzocchetti L, De Sensi F, Rossi A, Notarstefano P, *et al.* Ventricular tachycardia ablation guided or aided by scar characterization with cardiac magnetic resonance: rationale and design of VOYAGE study. *BMC Cardiovasc Disord* 2022;**22**:169.
63. Lin A, Manral N, McElhinney P, Killekar A, Matsumoto H, Kwiecinski J, *et al.* Deep learning-enabled coronary CT angiography for plaque and stenosis quantification and cardiac risk prediction: an international multicentre study. *Lancet Digit Health* 2022;**4**:e256–e265.
64. Williams MC, Weir-McCall JR, Baldassarre LA, De Cecco CN, Choi AD, Dey D, *et al.* Artificial intelligence and machine learning for cardiovascular computed tomography (CCT): a white paper of the Society of Cardiovascular Computed Tomography (SCCT). *J Cardiovasc Comput Tomogr* 2024;**18**:519–532.
65. van Velzen SGM, Lessmann N, Velthuis BK, Bank IEM, van den Bongard DHJG, Leiner T, *et al.* Deep learning for automatic calcium scoring in CT: validation using multiple cardiac CT and chest CT protocols. *Radiology* 2020;**295**:66–79.
66. Oikonomou EK, Williams MC, Kotanidis CP, Desai MY, Marwan M, Antonopoulos AS, *et al.* A novel machine learning-derived radiotranscriptomic signature of perivascular fat improves cardiac risk prediction using coronary CT angiography. *Eur Heart J* 2019;**40**:3529–3543.
67. Tesche C, De Cecco CN, Baumann S, Renker M, McLaurin TW, Duguay TM, *et al.* Coronary CT angiography-derived fractional flow reserve: machine learning algorithm versus computational fluid dynamics modeling. *Radiology* 2018;**288**:64–72.
68. Motwani M, Dey D, Berman DS, Germano G, Achenbach S, Al-Mallah MH, *et al.* Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. *Eur Heart J* 2017;**38**:500–507.
69. Moon JH, Lee DY, Cha WC, Chung MJ, Lee KS, Cho BH, *et al.* Automatic stenosis recognition from coronary angiography using convolutional neural networks. *Comput Methods Programs Biomed* 2021;**198**:105819.
70. Cong C, Kato Y, Vasconcellos HDD, Ostovaneh MR, Lima JAC, Ambale-Venkatesh B. Deep learning-based end-to-end automated stenosis classification and localization on catheter coronary angiography. *Front Cardiovasc Med* 2023;**10**:944135.
71. Ma X, Shibata Y, Kurihara O, Kobayashi N, Takano M, Kurihara T. Identifying pathogenesis of acute coronary syndromes using sequence contrastive learning in coronary angiography. *Am J Cardiol* 2026;**258**:89–99.
72. Rostami B, Fetterly K, Attia Z, Challa A, Lopez-Jimenez F, Thaden J, *et al.* Deep learning to estimate left ventricular ejection fraction from routine coronary angiographic images. *JACC Adv* 2023;**2**:100632.
73. Svennberg E, Friberg L, Frykman V, Al-Khalili F, Engdahl J, Rosenqvist M. Clinical outcomes in systematic screening for atrial fibrillation (STROKESTOP): a multicentre, parallel group, unmasked, randomised controlled trial. *Lancet* 2021;**398**:1498–1506.
74. Rizas KD, Freyer L, Sappler N, von Stülpnagel L, Spielbichler P, Krasniqi A, *et al.* Smartphone-based screening for atrial fibrillation: a pragmatic randomized clinical trial. *Nat Med* 2022;**28**:1823–1830.
75. Dörr M, Nohturfft V, Brasier N, Bosshard E, Djurdjevic A, Gross S, *et al.* The WATCH AF trial: SmartWATCHes for detection of atrial fibrillation. *JACC Clin Electrophysiol* 2019;**5**:199–208.
76. De La Torre Hernandez JM, Exposito V, Gonzalez Enriquez S, Rodriguez Entem F, Margarida A, García Camarero T, *et al.* Evaluation of ambulatory electrocardiographic monitoring of patients after high-risk acute coronary syndrome: the MONITOR ACS-Epic 13 randomized trial. *Front Cardiovasc Med* 2025;**12**:1646175.
77. Bauer A, Sappler N, von Stülpnagel L, Klemm M, Schreinlechner M, Wenner F, *et al.* Telemedical cardiac risk assessment by implantable cardiac monitors in patients after myocardial infarction with autonomic dysfunction (SMART-MI-DZHK9): a prospective investigator-initiated, randomised, multicentre, open-label, diagnostic trial. *Lancet Digit Health* 2022;**4**:e105–e116.
78. Hygrell T, Viberg F, Dahlberg E, Charlton PH, Kemp Gudmundsdottir K, Mant J, *et al.* An artificial intelligence–based model for prediction of atrial fibrillation from single-lead sinus rhythm electrocardiograms facilitating screening. *Europace* 2023;**25**:1332–1338.
79. Attia ZI, Noseworthy PA, Lopez-Jimenez F, Asirvatham SJ, Deshmukh AJ, Gersh BJ, *et al.* An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. *Lancet* 2019;**394**:861–867.
80. Galloway CD, Valys AV, Shreibati JB, Treiman DL, Petterson FL, Gundotra VP, *et al.* Development and validation of a deep-learning model to screen for hyperkalemia from the electrocardiogram. *JAMA Cardiol* 2019;**4**:428–436.
81. Ko WY, Siontis KC, Attia ZI, Carter RE, Kapa S, Ommen SR, *et al.* Detection of hypertrophic cardiomyopathy using a convolutional neural network-enabled electrocardiogram. *J Am Coll Cardiol* 2020;**75**:722–733.
82. Saglietto A, Gaita F, Blomstrom-Lundqvist C, Arbelo E, Dagres N, Brugada J, *et al.* AFA-Recur: an ESC EORP AFA-LT registry machine-learning web calculator predicting atrial fibrillation recurrence after ablation. *Europace* 2023;**25**:92–100.
83. Marijon E, Narayanan K, Smith K, Barra S, Basso C, Blom MT, *et al.* The Lancet Commission to reduce the global burden of sudden cardiac death: a call for multidisciplinary action. *Lancet* 2023;**402**:883–936.

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84. Bhagirath P, Strocchi M, Bishop MJ, Boyle PM, Plank G. From bits to bedside: entering the age of digital twins in cardiac electrophysiology. *Europace* 2024; **26**:euae295.
85. Chen Z, Ono N, Chen W, Tamura T, Altaf-Ul-Amin MD, Kanaya S, *et al.* The feasibility of predicting impending malignant ventricular arrhythmias by using nonlinear features of short heartbeat intervals. *Comput Methods Programs Biomed* 2021;**205**:106102.
86. Taye GT, Hwang HJ, Lim KM. Application of a convolutional neural network for predicting the occurrence of ventricular tachyarrhythmia using heart rate variability features. *Sci Rep* 2020;**10**:6769.
87. Shakibfar S, Krause O, Lund-Andersen C, Aranda A, Moll J, Andersen TO, *et al.* Predicting electrical storms by remote monitoring of implantable cardioverter-defibrillator patients using machine learning. *Europace* 2019;**21**: 268–274.
88. Doolub G, Khurshid S, Theriault-Lauzier P, Nolin Lapalme A, Tastet O, So D, *et al.* Revolutionizing acute cardiac care with artificial intelligence: opportunities and challenges. *Can J Cardiol* 2024;**40**:1813–1827.
89. Alrawashdeh A, Alqahtani S, Alkhatib ZI, Kheirallah K, Melhem NY, Alwidyan M, *et al.* Applications and performance of machine learning algorithms in emergency medical services: a scoping review. *Prehosp Disaster Med* 2024; **39**:368–378.
90. Sengupta S, Biswal S, Titus J, Burman A, Reddy K, Fulwani MC, *et al.* A novel breakthrough in wrist-worn transdermal troponin-I-sensor assessment for acute myocardial infarction. *Eur Heart J Digit Health* 2023;**4**:145–154.
91. Van Heuverswyn F, De Buyzere M, Coeman M, De Pooter J, Drieghe B, Duytschaever M, *et al.* Feasibility and performance of a device for automatic self-detection of symptomatic acute coronary artery occlusion in outpatients with coronary artery disease: a multicentre observational study. *Lancet Digit Health* 2019;**1**:e90–e99.
92. Herman R, Meyers HP, Smith SW, Bertolone DT, Leone A, Bermpeis K, *et al.* International evaluation of an artificial intelligence–powered electrocardiogram model detecting acute coronary occlusion myocardial infarction. *Eur Heart J Digit Health* 2024;**5**:123–133.
93. Muralitharan S, Nelson W, Di S, McGillion M, Devereaux PJ, Barr NG, *et al.* Machine learning-based early warning systems for clinical deterioration: systematic scoping review. *J Med Internet Res* 2021;**23**:e25187.
94. Zweck E, Thayer KL, Helgestad OKL, Kanwar M, Ayouty M, Garan AR, *et al.* Phenotyping cardiogenic shock. *J Am Heart Assoc* 2021;**10**:e020085.
95. Toy J, Bosson N, Schlesinger S, Gausche-Hill M, Stratton S. Artificial intelligence to support out-of-hospital cardiac arrest care: a scoping review. *Resusc Plus* 2023;**16**:100491.
96. Viderman D, Abdildin YG, Batkuldinova K, Badenes R, Bilotta F. Artificial intelligence in resuscitation: a scoping review. *J Clin Med* 2023;**12**:2254.
97. Aqel S, Syaj S, Al-Bzour A, Abuzanouneh F, Al-Bzour N, Ahmad J. Artificial intelligence and machine learning applications in sudden cardiac arrest prediction and management: a comprehensive review. *Curr Cardiol Rep* 2023;**25**: 1391–1396.
98. Kwon JM, Kim KH, Jeon KH, Lee SY, Park J, Oh BH. Artificial intelligence algorithm for predicting cardiac arrest using electrocardiography. *Scand J Trauma Resusc Emerg Med* 2020;**28**:98.
99. Holmstrom L, Bednarski B, Chugh H, Aziz H, Pham HN, Sargsyan A, *et al.* Artificial intelligence model predicts sudden cardiac arrest manifesting with pulseless electric activity versus ventricular fibrillation. *Circ Arrhythm Electrophysiol* 2024;**17**:e012338.
100. Park MJ, Choi YJ, Shim M, Cho Y, Park J, Choi J, *et al.* Performance of ECG-derived digital biomarker for screening coronary occlusion in resuscitated out-of-hospital cardiac arrest patients: a comparative study between artificial intelligence and a group of experts. *J Clin Med* 2024;**13**:1354.
101. Hajeb-M S, Cascella A, Valentine M, Chon KH. Deep neural network approach for continuous ECG-based automated external defibrillator shock advisory system during cardiopulmonary resuscitation. *J Am Heart Assoc* 2021; **10**:e019065.
102. Jaureguibeitia X, Zubia G, Irusta U, Aramendi E, Chicote B, Alonso D, *et al.* Shock decision algorithms for automated external defibrillators based on convolutional networks. *IEEE Access* 2020;**8**:154746–154758.
103. Isasi I, Irusta U, Aramendi E, Eftestøl T, Kramer-Johansen J, Wik L. Rhythm analysis during cardiopulmonary resuscitation using convolutional neural networks. *Entropy* 2020;**22**:595.
104. Hummel J, Houmsse M, Tomassoni G, Nair D, Romero J, Hargrove J, *et al.* A patch wearable cardioverter-defibrillator for patients at risk of sudden cardiac arrest. *J Am Coll Cardiol* 2024;**84**:525–536.
105. Ferguson T, Olds T, Curtis R, Blake H, Crozier AJ, Dankiw K, *et al.* Effectiveness of wearable activity trackers to increase physical activity and improve health: a systematic review of systematic reviews and meta-analyses. *Lancet Digit Health* 2022;**4**:e615–e626.
106. Mukkamala R, Shroff SG, Landry C, Kyriakoulis KG, Avolio AP, Stergiou GS. The Microsoft Research Aurora Project: important findings on cuffless blood pressure measurement. *Hypertension* 2023;**80**:534–540.
107. Stergiou GS, Mukkamala R, Avolio A, Kyriakoulis KG, Mieke S, Murray A, *et al.* Cuffless blood pressure measuring devices: review and statement by the European Society of Hypertension Working Group on Blood Pressure Monitoring and Cardiovascular Variability. *J Hypertens* 2022;**40**:1449–1460.
108. Walch O, Huang Y, Forger D, Goldstein C. Sleep stage prediction with raw acceleration and photoplethysmography heart rate data derived from a consumer wearable device. *Sleep* 2019;**42**:zsz180.
109. Mejía-Mejía E, Budidha K, Abay TY, May JM, Kyriacou PA. Heart Rate Variability (HRV) and Pulse Rate Variability (PRV) for the assessment of autonomic responses. *Front Physiol* 2020;**11**:779.
110. Topalidis PI, Baron S, Heib DPJ, Eigl ES, Hinterberger A, Schabus M. From pulses to sleep stages: towards optimized sleep classification using heart-rate variability. *Sensors* 2023;**23**:9077.
111. Palermi S, Vecchiato M, Saglietto A, Niederseer D, Oxborough D, Ortega-Martorell S, *et al.* Unlocking the potential of artificial intelligence in sports cardiology: does it have a role in evaluating athlete's heart? *Eur J Prev Cardiol* 2024;**31**:470–482.
112. Visseren FLJ, Mach F, Smulders YM, Carballo D, Koskinas KC, Bäck M, *et al.* 2021 ESC guidelines on cardiovascular disease prevention in clinical practice. *Eur Heart J* 2021;**42**:3227–3337.
113. Golbus JR, Lopez-Jimenez F, Barac A, Cornwell WK, Dunn P, Forman DE, *et al.* Digital technologies in cardiac rehabilitation: a science advisory from the American Heart Association. *Circulation* 2023;**148**:95–107.
114. Scherrenberg M, Falter M, Abreu A, Aktaa S, Busnatu S, Casado-Arroyo R, *et al.* Standards for cardiac telerehabilitation. *Eur Heart J* 2025;**46**:3714–3737.
115. Shi W, Green H, Sikhosana N, Fernandez R. Effectiveness of Telehealth Cardiac Rehabilitation Programs on Health Outcomes of Patients With Coronary Heart Diseases: *An Umbrella Review*. *J Cardiopulm Rehabil Prev* 2024;**44**:15–25.
116. Ozemek C, Strath SJ, Riggin K, Harber MP, Imboden MT, Kaminsky LA. Pedometer feedback interventions increase daily physical activity in phase III cardiac rehabilitation participants. *J Cardiopulm Rehabil Prev* 2020;**40**: 183–188.
117. Jenkins S, Cross A, Osman H, Salim F, Lane D, Bernieh D, *et al.* Effectiveness of biofeedback on blood pressure in patients with hypertension: systematic review and meta-analysis. *J Hum Hypertens* 2024;**38**:719–727.
118. Hammond-Haley M, Allen C, Han J, Patterson T, Marber M, Redwood S. Utility of wearable physical activity monitors in cardiovascular disease: a systematic review of 11 464 patients and recommendations for optimal use. *Eur Heart J Digit Health* 2021;**2**:231–243.
119. Omboni S, McManus RJ, Bosworth HB, Chappell LC, Green BB, Kario K, *et al.* Evidence and recommendations on the use of telemedicine for the management of arterial hypertension: *An International Expert Position Paper*. *Hypertension* 2020;**76**:1368–1383.
120. Kruizinga MD, Stuurman FE, Exadaktylos V, Doll RJ, Stephenson DT, Groeneveld GJ, *et al.* Development of novel, value-based, digital endpoints for clinical trials: a structured approach toward fit-for-purpose validation. *Pharmacol Rev* 2020;**72**:899–909.
121. Alawoad Z, Jensen J, Schou M, Ahmed N, Attia A, Rao S, *et al.* Redefining endpoints in heart failure clinical trials: the emerging role of wearable technologies in contemporary trial design. *Heart Fail Rev* 2025;**31**:1.
122. Coravos A, Khozin S, Mandl KD. Developing and adopting safe and effective digital biomarkers to improve patient outcomes. *NPJ Digit Med* 2019;**2**:14.
123. Ferrar J, Griffith GJ, Skirrow C, Cashdollar N, Taptiklis N, Dobson J, *et al.* Developing digital tools for remote clinical research: how to evaluate the validity and practicality of active assessments in field settings. *J Med Internet Res* 2021;**23**:e26004.
124. Padmanabhan S, Tran TQB, Dominiczak AF. Artificial intelligence in hypertension: seeing through a glass darkly. *Circ Res* 2021;**128**:1100–1118.
125. Fleming TR, Powers JH. Biomarkers and surrogate endpoints in clinical trials. *Stat Med* 2012;**31**:2973–2984.
126. Michelhaugh SA, Januzzi JL. Using artificial intelligence to better predict and develop biomarkers. *Heart Fail Clin* 2022;**18**:275–285.
127. Nahavandi D, Alizadehsani R, Khosravi A, Acharya UR. Application of artificial intelligence in wearable devices: opportunities and challenges. *Comput Methods Programs Biomed* 2022;**213**:106541.
128. Egger G, Dixon J. Beyond obesity and lifestyle: a review of 21st century chronic disease determinants. *Biomed Res Int* 2014;**2014:731685**.
129. Billings J, Blunt I, Steventon A, Georghiou T, Lewis G, Bardsley M. Development of a predictive model to identify inpatients at risk of readmission within 30 days of discharge (PARR-30). *BMJ Open* 2012;**2**:e001667.

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130. Jensen MT, Treskes RW, Caiani EG, Casado-Arroyo R, Cowie MR, Dilaveris P, *et al.* ESC working group on e-cardiology position paper: use of commercially available wearable technology for heart rate and activity tracking in primary and secondary cardiovascular prevention—in collaboration with the European Heart Rhythm Association, European Association of Preventive Cardiology, Association of Cardiovascular Nursing and Allied Professionals, Patient Forum, and the Digital Health Committee. *Eur Heart J Digit Health* 2021;**2**:49–59.
131. Dhingra LS, Aminorroaya A, Oikonomou EK, Nargesi AA, Wilson FP, Krumholz HM, *et al.* Use of wearable devices in individuals with or at risk for cardiovascular disease in the US, 2019 to 2020. *JAMA Netw Open* 2023;**6**:e2316634.
132. Farkowski MM, Scherr D, Boriani G, Kazakiewicz D, Haim M, Huculeci R, *et al.* Arrhythmia care in ESC member countries: the 2025 ESC-EHRA atlas on heart rhythm disorders. *Europace* 2025;**27**:euaf124.
133. Kawu AA, Hederman L, Doyle J, O'Sullivan D. Patient generated health data and electronic health record integration, governance and socio-technical issues: a narrative review. *Inform Med Unlocked* 2023;**37**:101153.
134. Boston D, Cohen D, Stone J, Edwards E, Brown A, Snow M, *et al. Integrating Patient-Generated Health Data into Electronic Health Records in Ambulatory Care Settings: A Practical Guide*. Rockville (MD): Agency for Healthcare Research and Quality (US); 2021. Prepared under Contract 75Q80120D00019/75Q80120F32001. AHRQ Publication No. 22-0013.
135. Nahra KJ, Corbin BA. Digital health regulatory gaps in the United States. *Compliance Elliance Journal* 2018;**4**:21–34.
136. Dudarev V, Barral O, Zhang C, Davis G, Enns JT. On the reliability of wearable technology: a tutorial on measuring heart rate and heart rate variability in the wild. *Sensors* 2023;**23**:5863.
137. Beckers R, Van Hoydonck P. Impact of the regulatory framework on medical device software manufacturers: are the guidance documents supporting the practical implementation? *Int J Health Policy Manag* 2023;**12**:7470.
138. Zhang S, Zhou X, Chen Y, Wang L, Zhu B, Jiang Y, *et al.* Changes in home blood pressure monitored among elderly patients with hypertension during the COVID-19 outbreak: a longitudinal study in China leveraging a smartphone-based application. *Circ Cardiovasc Qual Outcomes* 2021;**14**:e007098.
139. Nomura A, Tanigawa T, Kario K, Igarashi A. Cost-effectiveness of digital therapeutics for essential hypertension. *Hypertens Res* 2022;**45**:1538–1548.
140. Zakiyah N, Marulin D, Alfaqeeh M, Puspitasari IM, Lestari K, Lim K, *et al.* Economic Evaluations of Digital Health Interventions for Patients With Heart Failure: *Systematic Review*. *J Med Internet Res* 2024;**26**:e53500.
141. Zhang Y, Peña MT, Fletcher LM, Lal L, Swint JM, Reneker JC. Economic evaluation and costs of remote patient monitoring for cardiovascular disease in the United States: a systematic review. *Int J Technol Assess Health Care* 2023;**39**:e25.
142. Guthrie NL, Carpenter J, Edwards KL, Appelbaum KJ, Dey S, Eisenberg DM, *et al.* Emergence of digital biomarkers to predict and modify treatment efficacy: machine learning study. *BMJ Open* 2019;**9**:e030710.
143. CTTI. Developing Novel Endpoints [Internet]. [cited 2024 Feb 8]. https://ctti-clinicaltrials.org/our-work/digital-health-trials/developing-novel-endpoints/
144. Chang EM, Gillespie EF, Shaverdian N. Truthfulness in patient-reported outcomes: factors affecting patients' responses and impact on data quality. *Patient Relat Outcome Meas* 2019;**10**:171–186.
145. Luo H, Yang D, Barszczyk A, Vempala N, Wei J, Wu SJ, *et al.* Smartphone-based blood pressure measurement using transdermal optical imaging technology. *Circ Cardiovasc Imaging* 2019;**12**:e008857.
146. Zhang L, Yuan M, An Z, Zhao X, Wu H, Li H, *et al.* Prediction of hypertension, hyperglycemia and dyslipidemia from retinal fundus photographs via deep learning: a cross-sectional study of chronic diseases in central China. *PLoS One* 2020;**15**:e0233166.
147. Golovchiner G, Glikson M, Swissa M, Sela Y, Abelow A, Morelli O, *et al.* Automated detection of atrial fibrillation based on vocal features analysis. *J Cardiovasc Electrophysiol* 2022;**33**:1647–1654.
148. Sara JDS, Maor E, Orbelo D, Gulati R, Lerman LO, Lerman A. Noninvasive voice biomarker is associated with incident coronary artery disease events at follow-up. *Mayo Clin Proc* 2022;**97**:835–846.

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