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DIGITAL TECHNOLOGIES IN HEART FAILURE CARE: ARTIFICIAL INTELLIGENCE, REMOTE MONITORING, AND SOCIAL IMPLICATIONS FOR EQUITABLE CARDIOVASCULAR HEALTH — A NARRATIVE REVIEW OF THE LITERATURE, 2022–2026

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ABSTRACT

Digital health has advanced dramatically since 2022 and will continue until 2026; this paper is a review of clinical use, implementation challenges, and social implications of digital health for patients with heart failure (HF). Literature was reviewed from January 1, 2022 to March 31, 2026. Priority was placed on publications by major international organizations (World Health Organization [WHO], American Heart Association [AHA], European Society of Cardiology [ESC] etc.) and peer-reviewed indexed journals focused on HF including diagnosis, risk stratification, surveillance, self-care, and health disparities. Artificial intelligence (AI) appears to improve ECG screening, imaging interpretation, and multimodal phenotyping and short term risk prediction. Structured remote monitoring systems also have been demonstrated to reduce hospitalizations and mortality when applied within defined clinical pathways. Telemedicine and wearable devices appear to be effective tools to support patient self-management and enhance follow up. However, both are highly dependent on many factors, including: digital literacy, reimbursement, staffing levels, device compatibility, and institutional structure. In addition, the literature suggests that a digital transformation will exacerbate existing inequities unless these technologies are designed to address the barriers of age, language, socioeconomic status, algorithmic bias, and unequal access to technology and the internet.

KEYWORDS

Heart Failure; Artificial Intelligence; Telemedicine; Remote Monitoring; Wearable Devices; Digital Health Equity

CITATION

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1. Introduction

Heart Failure is an extensive disease condition that will result in either one or both ventricles failing to adequately fill with blood during diastole (diastolic dysfunction) or pump out blood from the ventricles during systole (systolic dysfunction). Pharmacological and device therapies for heart failure have progressed dramatically but still, most patients receive traditional care based on intermittent assessments at clinics. Technology can be developed that identifies subtle changes in blood pressure, rhythm, activity, weight, respiratory patterns or symptoms reported by the patient and could allow clinicians to intervene before the patient's condition deteriorates further, and possibly avoid trips to the Emergency Department and hospitalizations. The existing digital framework of heart failure utilizes AI/ML on ECGs, echocardiography, multimodal imaging, EHRs, and wearable sensors as well as remote monitoring platforms for transmitting symptom surveys and physiological data to clinicians. Telemedicine also allows clinicians to remotely manage medication titration, patient self-care, cardiac rehabilitation and post-discharge follow up. These advancements collectively represent a broader movement towards decentralized, data-driven, and personalized management of chronic cardiovascular disease. (Armoundas et al., 2024; Masotta et al., 2024; Ginsburg et al., 2024).

The value of digitalization is not inherent. For technology-based care to work, there must be an available device, a stable internet connection, technical support, linguistically accessible interfaces, and a willingness on the part of the patient to share personal health information. In addition, highly effective algorithms developed using controlled datasets may prove less effective in real-world settings because of limited population diversity, fragmented data sources, or poor alignment between the clinical workflow and the needs of clinicians. Therefore, the central question is no longer whether digital technologies can be applied to heart failure, but under what conditions they can improve outcomes without increasing inequities. This review was conducted to examine digital technologies in heart failure both as technical instruments and as components of broader care models shaped by social determinants of health, institutional capacity, regulatory frameworks, financial arrangements, and the relationship between technology and society. The 2022-2026 period is particularly relevant because it includes the post-COVID era, the rapid maturation of wearable and AI technologies, and several major scientific statements published during this interval. (Kim et al., 2024; Monlezun et al., 2025; Nair et al., 2025; World Health Organization, 2021; World Health Organization, 2025).

The goals of this review are to summarize current research on AI in the diagnosis, phenotyping, risk assessment, and prediction of heart failure; evaluate remote monitoring methods such as telehealth platforms, wearable devices, and implantable hemodynamic sensors; assess the societal impact of these technologies, particularly the potential for digital disparities and algorithmic bias; and outline a data-informed framework for integrating digital technology into heart failure care in a fair and clinically relevant manner.

2. Methodology

This manuscript was prepared as a narrative review of literature published between January 2022 and March 2026. The review was designed to synthesize clinically relevant, implementation-relevant, and policy-relevant evidence on digital technologies in HF, with particular emphasis on AI, telehealth, remote physiologic monitoring, wearable technologies, patient self-management, health equity, and the organization of care.

The literature informing this review was identified through targeted searches of official scientific and policy documents and peer-reviewed biomedical literature. Priority was given to documents issued by the European Society of Cardiology (ESC), the American Heart Association (AHA), and the World Health Organization (WHO), as well as to indexed publications retrieved primarily through PubMed/MEDLINE and reference-list screening of relevant reviews, statements, and original investigations. Search terms included combinations of "heart failure," "artificial intelligence," "machine learning," "electrocardiography," "imaging," "remote monitoring," "telemedicine," "wearables," "digital health equity," "implementation," "social determinants of health," "reimbursement," and "policy." Literature identification and source updating were carried out during manuscript development and were updated through March 2026. Eligibility for inclusion was based on topical relevance to diagnosis, monitoring, implementation, health equity, or health-system design in heart failure. Clinical guidelines, scientific statements, systematic reviews, meta-analyses, high-quality narrative reviews, and selected original studies were considered eligible when they provided clinically actionable, implementation-relevant, or policy-relevant information. Sources of limited relevance to heart failure, unclear methodology, or minimal implementation relevance were not incorporated into the final synthesis. Titles and abstracts were reviewed by the authors for relevance, and full texts were assessed when additional detail was required to determine eligibility or interpret applicability. Because the included literature comprised heterogeneous study designs, technologies, endpoints, and implementation settings, the review followed a narrative rather than quantitative synthesis. Accordingly, this manuscript does not claim the methodological completeness of a systematic review; instead, it uses a structured, evidence-based approach to integrate clinical evidence with literature on implementation science, digital inclusion, and health policy.

3. Results of the review

3.1. The contemporary clinical context of heart failure digitalization

HF is an ideal area for digital enhancement due to the fact that status changes occur over time, often outside of clinical environments. The progression from congestive heart failure to overt symptoms is often unpredictable; there is significant variability in patients' ability to adhere to prescribed medications and treatments; many patients have multiple comorbid conditions contributing to their health issues; and the process of managing HF involves continuous adjustments to diuretic therapy, disease-modifying drugs, and other supportive therapies. In traditional HF management, there is typically a considerable gap between the point at which a patient's physiologic status deteriorates and the point at which he or she receives clinical evaluation. This delay contributes to unnecessary hospitalizations and to a focus on reactive versus preventative care. (Teleanu et al., 2025; McDonagh et al., 2023; Masotta et al., 2024).

Since 2022, the literature has been shifting its focus away from HF as simply an episodic event that requires increased intensity of treatment, to seeing HF as a longitudinal data issue. In essence, this means that while one may need to monitor additional variables, it is necessary to tie these variables to timely actions. This paradigmatic shift is reflected in the increasing emphasis on "digital tools" that provide a holistic approach to the patient journey from screening and diagnosis to treatment optimization, monitoring and implementation support. Therefore, the focus of the field is increasingly focused on designing systems as well as developing sensors. (Myhre et al., 2024).

However, the literature also clearly shows that the effectiveness of technology in improving outcomes is directly dependent on the specific program design. For example, remote monitoring will be more successful when it is part of a structured clinical pathway than when data collection occurs without clear escalation plans. Similarly, AI will perform optimally when models are externally validated, clinically relevant, and employed in specific decision-making contexts rather than as general risk assessment tools. Thus, the fundamental question becomes not how much data can be generated, but rather how to transform them into timely, reliable and equitable care. This theme continues throughout the sections that follow. (De Lathauwer et al., 2025; Cajita et al., 2026; Myhre et al., 2024; Masotta et al., 2024).

3.2. Artificial intelligence in heart failure care

3.2.1. Conceptual role of AI in HF

AI in HF encompasses a wide spectrum of methods, from supervised machine learning models built on structured clinical variables to deep learning systems trained on raw waveforms or imaging data. The most clinically relevant use cases in recent literature include: screening for ventricular dysfunction from ECG; automated image acquisition and interpretation; phenotyping of heterogeneous HF populations, especially HF with preserved ejection fraction (HFpEF); prediction of incident HF; estimation of hospitalization or mortality risk; and identification of patterns of deterioration from multimodal remote-monitoring data. The 2024 AHA scientific statement on the use of AI in improving outcomes in heart disease provides an important conceptual framework. It argues that AI can contribute across the continuum of diagnosis, classification, and treatment, but emphasizes that few tools have yet demonstrated sufficient outcome benefit for widespread adoption. This is a crucial point. In HF, predictive accuracy alone is not the target. The target is clinically actionable prediction that improves care without increasing unnecessary testing, alert fatigue, or inequity. Accordingly, the most promising AI applications are those that either uncover otherwise missed disease or support decisions in settings characterized by information overload. (Armoundas et al., 2024; Alyacoub et al., 2025; Medhi et al., 2024).

3.2.2. AI-enabled electrocardiography

AI-enhanced ECG analysis currently represents one of the greatest opportunities for scalability among all contemporary uses of AI.

ECGs offer several practical advantages, including low cost, wide availability, and integration into routine care. In addition, AI models can detect latent characteristics in ECG data that would not be visible to human readers and may identify patterns related to left ventricular systolic dysfunction, diastolic dysfunction, elevated filling pressure, or future HF risk.

In 2025, Dhingra and colleagues presented data on a noise-adjusted AI model which was able to estimate HF risk using single-lead ECGs from multiple international populations. This indicates the possibility of portable, and wearable ecg based HF risk assessment.

In 2026, Desai and colleagues provided evidence that the use of AI in combination with the analysis of 12-lead ECGs resulted in better prediction of incident HF compared to the use of clinical risk factors alone, in pooled analyses of the HeartShare/AMP-HF studies.

These results are important because they indicate a possible pathway for connecting the traditional cardiovascular disease prevention paradigm with digital screening paradigms. The potential exists to identify people at higher risk for developing HF, so that they can receive further testing with echocardiography, or enhanced control of their HF risk factors. (Desai et al., 2026; Dhingra et al., 2025; Sau et al., 2024).

While AI-ECG presents the promise of both diagnosis/prognosis and a possible path forward for deploying AI in healthcare, it has many challenges. The first challenge is that the performance of AI models may vary by different device manufacturers, acquisition environment and demographics.

The second challenge is defining how a positive AI signal will relate to pathways of care. For example, who receives confirmatory imaging, at what level of probability, and what resources will be required to implement this pathway?

The third challenge relates to the possibility that the probability generated by an AI model will be viewed as a definitive diagnosis, when in fact, it should serve as a trigger for a structured process of investigation. Without proper implementation, the benefits associated with increases in sensitivity may be offset by increased testing, and variability in follow-up. (Dhingra et al., 2025; Desai et al., 2026).

3.2.3. AI in imaging and automated phenotyping

AI is being used across multiple stages of cardiovascular imaging. The 2024 AHA Scientific Statement on value creation through AI and cardiovascular imaging highlights opportunities spanning test selection, image acquisition, segmentation, interpretation, and prognostic modeling. These applications are highly relevant to heart failure because imaging is central to classification by ejection fraction, identification of structural heart disease, assessment of remodeling and congestion, and evaluation of etiology. AI may also reduce interobserver variability, shorten analysis time, standardize measurements, and extract additional prognostic features from imaging datasets. (Hanneman et al., 2024)

Heart failure with preserved ejection fraction (HFpEF) is the most clinically heterogeneous form of heart failure. This heterogeneity has complicated both trial interpretation and individualized management. Machine-learning-based phenotyping has therefore received substantial attention. In 2024, Pierre-Jean and colleagues showed that AI-derived phenotypes could stratify risk and potentially guide more targeted management when derived from electronic health record and echocardiographic data. Such work forms part of a broader effort to move beyond syndromic categories and develop multidimensional biological and clinical subtypes. This approach is attractive because patients classified as having HFpEF likely represent several distinct pathophysiologic clusters with different comorbidity burdens, treatment responses, and clinical trajectories. However, the transition from phenotyping to improved care is not automatic. Cluster derivation may be statistically elegant yet clinically fragile, with results that depend heavily on local data architecture, variable selection, and retrospective labeling. For phenotypes to become practice-changing, they must be reproducible across settings, linked to modifiable management decisions, and shown to improve outcomes compared with standard classification. Current evidence therefore supports AI-based phenotyping primarily as a promising research and risk-enrichment tool rather than as an established determinant of routine treatment selection. (Yi & Cho, 2026; Pierre-Jean et al., 2024)

3.2.4. Multimodal prediction and prognosis

HF generates a wide range of multimodal data such as lab results, biomarkers, medications, imaging, devices, patient symptoms, and increasingly, wearable signals. AI has significant potential to analyze and integrate all these different types of data. There have been numerous articles describing models that include data such as clinical notes, images, and physiological measures to predict readmission, mortality, or progression. Articles and reviews published in 2024-2026 emphasize that while AI can be used to assist with the clinician's decision-making process, its greatest strength is in recognizing patterns in vast amounts of data that clinicians cannot manually synthesize. Thus, prognostic AI in HF could potentially aid in identifying high-risk patients requiring increased intensity of follow-up post-discharge, those who would benefit from advanced therapies, and those most likely to benefit from close remote monitoring. However, predictive models are only useful if they affect how clinicians manage their patients. For example, a mortality score will not lead to improved outcomes unless it leads to a change in treatment. The future of AI in HF therefore is likely to be through what we refer to as "care-coupled analytics," which will be predictive models that guide pathway decisions (e.g. when to adjust medication dosages, when to make referrals, when to escalate diagnostic testing, etc.) and/or trigger interventions such as nurse led outreach. The distinction between clinically relevant AI and purely technologically impressive but low impact AI is likely to be whether the AI is capable of triggering an intervention. (Alyacoub et al., 2025; Zhang et al., 2026).

3.2.5. Limitations of current AI evidence

The development of AI applications in HF is rapidly growing, but many have been similarly impacted by the same types of constraints. Models are typically created after a fact, and are then tested and validated within the model itself rather than being created and then tested prospectively. Most models have had very little external validation. There are no standard reporting guidelines, and often clinical relevance has not been incorporated into the application. Performance of models is commonly measured using metrics such as the area under the receiver operating characteristic curve. These measures do not directly measure the calibration, fairness, interpretability, or impact on the physician's ability to make decisions. Many training data sets used to develop models are limited in their diversity and include mostly young men, and therefore may be less representative of the elderly woman with frailty, racial and ethnic minority, or patient who receives care in a non-tertiary center. These are important to consider since HF is extremely prevalent in the populations that are at greatest risk for having underrepresented groups in digital data bases. Additionally, AI has a cost associated with the workflow. All alerts and risk estimates compete for the physicians' time and if they add to the physician's work load, and there is not a clear pathway for action, there is likely to be minimal acceptance. Governance, transparency, and multidisciplinary assessment were all emphasized by the AHA statement and subsequent reviews. It is anticipated that in order to successfully apply AI to HF, prospective trials will need to be conducted in practical settings, the output from the AI needs to be clinically understandable, and the performance of the AI needs to be explicitly monitored in subgroups. Currently, the evidence supports cautiously optimistic views regarding AI, which is promising clinically, but is currently in its early stages of translation for most HF use cases. (Armoundas et al., 2024; Alyacoub et al., 2025; Medhi et al., 2024)

3.2.6. AI, explainability, and clinical acceptability

There has been an ongoing debate in the development of HF AI regarding the gap between the reliability of the output of statistical models and the willingness of clinicians to rely upon these models at the bedside. Clinicians will generally be willing to utilize complex models as long as they can demonstrate their reliability, as well as the purpose they were created for; however, the slow rate of adoption of such models is attributed to the fact that many clinicians do not find them transparent or connected to a commonly accepted form of reasoning. Explainability of the statistical model's predictions does not necessitate that the clinician see every individual parameter of the deep neural network. Instead, explainability relates to providing the clinician with an understanding of what the statistical model is attempting to predict, the population that the model was trained on, the types of errors that would occur using the statistical model, and the resultant operational consequences of taking action based upon the results. In HF, where decisions may include referring to other services (specialist), escalating to additional diagnostic studies (echocardiogram, CT scan), modifying medications (diuretics) and prioritizing patients for follow-up evaluation, this level of acceptance is critical. The recent developments in AI-ECG illustrate the issue well. For example, a statistical model may accurately discriminate between individuals with and without latent probabilities of developing ventricular dysfunction or future heart failure. However, clinicians will still need to determine if this warrants further investigation through echocardiography, natriuretic peptide testing, increased surveillance or simply contextual discussions. Therefore, regardless of how strong the model performs, if the actionable outcome of utilizing the model is not clearly defined, uncertainty is likely to remain. Conversely, when the outputs of the statistical models are directly related to clear and defined protocolized next steps, utilization of the model becomes much more reasonable. Therefore, future HF AI development should focus not only on technical advancements, but also on integrating the output of the statistical model into standard care pathways. (Armoundas et al., 2024; Desai et al., 2026; Sau et al., 2024).

3.2.7. Sex- and gender-related considerations

While this study considers digital technologies in general, sex and gender issues require a specific focus. There are many ways in which digital health equity for cardiovascular disease can impact women and men differently. For example, women may both easily adopt digital tools and be less likely than men to be referred to clinically based digital interventions. Women have historically represented a higher percentage of HFpEF patients and women in HFpEF have historically experienced prolonged recognition/delayed diagnosis. If AI models are developed using datasets with insufficient representation of women with variable symptom presentations and comorbidities, then there is an increased risk of developing models with reduced sensitivity/calibration in the exact patient population where model development could provide the greatest benefits. Therefore, sex-specific validation (sex-disaggregated) should be a standard part of validating any digital studies related to heart failure. Investigators should not only report subgroup data by sex; they should also determine whether the enrollment process, application design, language used, and burden of care, as well as symptom capture in digital studies accurately reflect women's experience with heart failure. (Yi & Cho, 2026; Kim et al., 2024).

3.3. Remote monitoring and telehealth in heart failure

3.3.1. Rationale for remote monitoring

Remote monitoring has been appealing to many for use in HF due to the fact that changes in physiology precede decompensation. Monitoring feasibility has evolved into the discussion regarding "which" models of monitoring are effective and for whom, as well as "under what" organizational conditions. Most current remote monitoring programs include some combination of symptom reporting, weight and/or blood pressure transmissions, video visits, education modules, wearable sensors, mobile apps and/or implantable pressure monitoring systems. Systematic reviews and meta-analyses have produced the best evidence on remote monitoring in HF patients over the last few years (as opposed to additional individual trials), indicating a field in the phase of implementation and refinement vs. first principles. A 2024 systematic review and meta-analysis by Masotta et al. demonstrated an association between telehealth care and remote monitoring for HF patients and decreased rates of mortality and rehospitalization. De Lathauwer et al. conducted a 2025 meta-analysis and suggested that there was a possible reduction in mortality and the first time HF hospitalizations with remote patient monitoring; and the potential benefit of remote patient monitoring appeared to be greater when interventions included self-management support, educational modules and video communication. These findings indicate that remote monitoring does not appear to simply collect signals. Rather, it appears that the most plausible benefits are achieved when remote monitoring is incorporated with both patient activation and human response. (Masotta et al., 2024; De Lathauwer et al., 2025; Teleanu et al., 2025; Cajita et al., 2026).

3.3.2. What makes remote monitoring effective?

In addition to differences in the technology used (e.g., wearable vs. mobile), differing metrics (e.g., physical activity vs. medication compliance) and different threshold values (e.g., 60% of predicted maximum oxygen consumption), differing levels of staff support (e.g., nurse vs. pharmacist), and varying time-to-response (e.g., <1 hour vs. >12 hours), also contribute to the variability across studies. These elements have been clarified using recent meta-analysis on the components related to better outcomes. Patient education and self-management content likely increase patient knowledge regarding their symptoms, compliance, and escalation behaviors. Video-based communication likely improves engagement, allows functional assessments, and provides relational continuity. Structured clinical decision making, as well as clinical oversight, ensure that abnormal trends lead to actionable decisions, such as adjusting diuretics, reviewing the patient urgently, or reinforcing diet and adherence. (Masotta et al., 2024; De Lathauwer et al., 2025).

3.3.3. Non-invasive remote monitoring

The non-invasive remote monitoring area has grown significantly in sophistication in the years between 2022 and 2026. Recent work in addition to traditional scales and blood pressure cuffs, have included; smartphone linked ECGs, wearable heart rhythm sensors, multisensor patch technology for respiratory monitoring, and thoracic bioimpedance. The reviews written in 2025 and 2026 show that there has been a shift from a static measurement model to a model of continuous or nearly continuous surveillance. The continuous or nearly continuous surveillance model could be particularly beneficial for patients who have been discharged from a hospital setting and experience recurring episodes of congestive heart failure since their risk of developing congestive heart failure is higher than at any other time, and their need for therapy can evolve quickly. Both thoracic bioimpedance and multisensor wearable technology are of particular interest since both technologies have the ability to detect fluid buildup or hemodynamic changes prior to symptom development. A systematic review written in 2024 evaluating bioimpedance based wearable technology found that while the concept is promising, evidence related to the technology remains very limited and heterogeneous. Similarly, a 2025 meta analysis evaluating wearable technology to identify and monitor pulmonary congestion also demonstrated that use of this type of technology resulted in fewer hospitalizations and cardiac-related events due to heart failure, although the number of participants in these studies were too low to draw definitive conclusions. Thus, these results should be viewed as positive indicators of future potential benefits, rather than current standard practices for patient care. (Scagliusi et al., 2024; Noci et al., 2025; Gaona et al., 2024).

3.3.4. Implantable hemodynamic monitoring

Implantable pulmonary artery pressure (PAP) monitoring for heart failure (HF) has a unique position among HF remote monitoring technologies. PAP is a direct measure of a pathophysiological process. Reviews from 2025 indicate that the use of pulmonary artery pressure to guide clinical decision-making will allow clinicians to detect increasing left ventricular filling pressures prior to clinical symptoms developing and will allow for intensified therapy prior to overt decompensation. Clinically useful features of these systems include both the ability to detect actionably trending hemodynamics and the opportunity to develop individually tailored diuresis and vasodilation strategies. Contemporary reviews regarding CardioMEMS and similar systems have also discussed the practicality of the system in the real-world as well as reported improvements in quality of life by patients. While implantable monitoring systems provide valuable information to the clinician, they are not a universal solution. They require resources such as the technical capability to perform procedures, the appropriate selection of patients, reimbursement mechanisms, and experienced personnel to manage post-procedure care. Furthermore, implantable systems typically require greater resources than non-invasive methods. Therefore, their optimal use may be in carefully selected high risk patients who experience recurrent decompensation despite receiving specialist follow-up, rather than as a population based approach. From a health equity perspective, this creates an important conflict: advanced technologies that are likely to be effective may also be used in those systems and populations that are already better funded. Thus, while implantable monitoring can provide clinically meaningful data, HF digitalization that is equitable cannot rely entirely on expensive technologies. (Bayes-Genis et al., 2025; Tolu-Akinnawo et al., 2025).

3.3.5. Telemedicine, virtual HF clinics, and post-discharge care

Telemedicine has been discussed in conjunction with monitoring, yet, it warrants its own consideration due to its impact on how we have access to care, regardless of whether we use new sensors. Remote virtual heart failure (HF) care enables early post-hospitalization review; reconciliation of medications; adjustments of guideline-directed therapies; discussion of symptoms; and rapid re-assessment after changing diuretic doses or renal function. For frail patients or patients who live at a distance from specialty clinics, telemedicine may improve the logistics of continuous care. Post-pandemic telemedicine literature supports the idea that telemedicine will be most effective when part of a hybrid model of care, rather than a total replacement of in-person evaluation. Some clinical judgment in HF remains contingent upon the need for physical exam, imaging, or lab testing. Conversely, numerous aspects of routine and semi-urgent management can be performed remotely using home-measured parameters, and well-defined escalation pathways. As such, it is likely that the model of the future of telemedicine will not be solely "digital", but rather stratified hybridity: matching the level of intensity and type of follow up to each patient's risk, capabilities and treatment phase. (Teleanu et al., 2025; Masotta et al., 2024; Masterson Creber et al., 2023).

3.3.6. Post-discharge vulnerability and transitional care

The best time to introduce an electronic tool for digital HF management is during the immediate post-hospital discharge phase. This is because the transition from an inpatient setting (where medical care was provided by the staff) to an outpatient/ambulatory self-care setting is medically fragile. Patients may have recently had their medications changed, patients' renal function may still be changing, and patients may be unsure what their target weight is, how much sodium they can consume, and when to call for assistance. Telemedicine/telehealth and remote monitoring can provide support during this "transition" period by providing additional contact with patients and/or providers during a period of high risk of non-compliance. Also, from a physiologic/pathophysiologic perspective, there is evidence that latent congestion may continue to exist even though patients appear clinically improved at the time of discharge. Monitoring of the patient's condition via non-invasive means and hemodynamic monitoring may assist in identifying patients who do not fully decongestate or who are experiencing early signs of relapse. Success of transitional care, however, relies heavily on response. An electronic reminder that goes unreviewed for several days has minimal benefit. Thus, a hospital-to-home pathway using digital technology should include a process for "on-boarding" prior to discharge, responsibility for first review of data, criteria for adjusting medications, and methods of communication regarding urgent changes. More recent literature supports that use of digital transitions is most successful if they occur prior to discharge as opposed to being added after discharge. (Masotta et al., 2024; Teleanu et al., 2025).

3.3.7. Data overload and alert fatigue

The very technology that allows for earlier detection of potential problems may be creating an excessive amount of "noise". The same HF monitoring systems that could send out weight loss/gain messages with no correlation to congestion, activity levels with no relationship to heart failure, or device-related issues interpreted as true changes, create false positive alarms. As a result, if the alert threshold is set too low (i.e., over-sensitive) or is not appropriate for the individual, clinicians will likely experience repeated low-specificity alerts from the monitoring platform. These repeated low-specificity alerts will likely lead to a decrease in the clinician's focus on the platform and eventually reduce their confidence in using it. Therefore, alert fatigue is not simply an issue of user-friendliness, but a key factor in determining the overall effectiveness of the monitoring platform. Thus, when developing a program, designers should consider the baseline variability of the patient population being monitored, use trend-based thresholds (as opposed to a single point-in-time), and develop a model for reviewing the lower level alerts before they escalate to higher levels of concern. The next wave of research in this area should move away from assessing whether monitoring detects change and begin to evaluate how monitoring can maximize the number of clinically relevant responses. (De Lathauwer et al., 2025; Teleanu et al., 2025).

3.4. Wearables, patient engagement, and self-management

3.4.1. Wearables entering clinical care

As wearable digital health technologies move into the clinical environment, the 2024 NEJM review of key issues related to their entry into clinical practice has provided a larger framework that is very relevant to HF. Wearable technologies can collect data regarding rhythms, activities, sleep, heart rates, variability, and in some instances ECG or physiologic surrogates related to the patient's congested state. One potential benefit of wearable technologies is their ability to provide the clinician with information about the patient's lived cardiovascular state, including how it changes between clinic visits. Since symptoms of HF and the patient's level of physical activity vary over time and since self-care plays an important role in managing the condition, having access to this type of information may be particularly beneficial. However, the wearable technology used by consumers and the wearable technology used by clinicians (e.g., hospital or doctor's office) exist within different evidence-based environments. While consumer wearable technologies may have the potential to increase patient engagement and provide trend data, they are not always supported with the necessary validation to support clinical decision-making in HF populations with edema, arrhythmias, or low output states. Therefore, the clinician will continue to experience a common dilemma: patients are increasingly presenting with data generated from wearable technologies; however, the interpretive and legal frameworks required to utilize these data are continuing to evolve. Guides published in 2025 on using consumer wearable technologies in cardiovascular medicine suggest that when utilizing these devices, the clinician should thoughtfully apply them, noting the need for device-specific validation, awareness of data quality, and the avoidance of excessive monitoring. (Ginsburg et al., 2024; Jamieson et al., 2025; Gaona et al., 2024; Nazir et al., 2025).

3.4.2. Self-care, adherence, and digital behavior support

The impact of how well patients manage their heart failure (HF) has much to do with how well they can self-manage. Self-management consists of several key elements such as managing medications; restricting sodium and fluids; identifying symptoms of worsening HF; tracking their weight; and communicating with the care team at appropriate times. Digital self-management tools can help to enhance some of these self-management areas through the use of reminder tools; structured education; tools to track symptoms; and personalized feedback. In 2024, Tunis et al. reviewed digital health technologies used in the management of HF self-management from a digital health equity perspective and stated that while app availability certainly impacts engagement, so too does social context; motivation; trust; usability; and supporting systems, all of which affect the extent to which digital self-care tools will result in meaningful changes in behavior. This is important because many times, when an individual fails to engage with a digital tool, researchers or clinicians often conclude that the patient was simply uninterested in using the tool. In fact, lack of engagement may have resulted from one of many factors including; designing tools that were inaccessible to the users; over-burdening users cognitively; designing tools with language that did not match the users' needs; providing inadequate on-boarding processes; or designing tools that did not meet the users' needs based upon their constraints of time and other aspects of daily life. Therefore, the most successful self-management digital tools for individuals with HF will likely be those that reduce complexity rather than increase it. For instance, tools that provide short symptom prompts; reminders to take medication at specific times; and easy access to nursing support, will likely be more beneficial to patients than tools with numerous features that require a great deal of user interaction. Therefore, the design philosophy for digital HF tools should focus on enhancing clinical relevance, reducing the amount of burden placed on the user, and being responsive to the diverse needs of users. (Tunis et al., 2024; Powell-Wiley et al., 2025; Kim et al., 2024).

3.4.3. Remote cardiac rehabilitation and functional monitoring

Although many studies regarding digital cardiac rehabilitation have focused on larger, general cardiovascular patient populations, there is a substantial amount of evidence supporting this type of rehabilitation for Heart Failure (HF) patients. The benefits of digital or remote exercise programs in increasing accessibility for patients that cannot participate in center-based care programs for heart failure is significant. It is significant because functional status, frailty, and deconditioning significantly impact trajectories of heart failure. As well, American Heart Association (AHA) statements, along with other publications in the field of cardiovascular rehabilitation are increasingly recognizing remote, digital rehabilitation as part of an overall continuum of technological support for cardiovascular behavior change. Remote rehabilitation programs for HF may provide an additional method of monitoring and assessing the effects of remote monitoring through providing not only early detection of increased risk, but also promoting long term resiliency, and improving quality of life. (Gaona et al., 2024; Nazir et al., 2025).

3.4.4. Patient-reported outcomes and symptom intelligence

HF severity cannot be determined solely by physiological metrics. Symptoms such as breathlessness, fatigue, edema perception, dizziness, appetite change, sleep disruption, and emotional distress each affect a patient's subjective experience and may occur prior to the time of first hospital visit. Therefore, a digital collection of patient-reported outcomes (PROs) can serve as an important addition to passive sensing. Repeated brief symptom assessments can provide the context for interpreting physiological trends and potentially allow clinicians to recognize early signs of worsening symptoms than would be possible through clinic-based reviews alone. Additionally, PROs may identify treatment burden (such as hypotension related fatigue post intensification of medications), which may not be detectable through only biometric systems. One major benefit of integrating PROs into digital systems for HF management is that it will continue to provide the patient's voice within increasingly automated systems of care. This has both ethical and clinical implications. Management of HF involves making trade-offs regarding objective reduction in risk versus the patient's tolerance of treatments and their ability to maintain daily functions and prioritize what is most important to them. Therefore, digital systems that include both passive monitoring of the patient and input from brief patient-reported symptom and quality of life assessments may better facilitate person-centered care than those that focus only on the capture of signals. (Tunis et al., 2024; Noci et al., 2025).

3.4.5. Caregivers and household context

The majority of the time, neither the health provider nor the patient manages HF care independently. The assistance of family members and informal caregivers in the management of HF care for patients is often needed. They assist with medication, doctor visits, diet, monitoring of symptoms, and the installation and maintenance of equipment (digital devices). Many designers of digital HF programs however design their digital HF programs based upon an individual as being the only user. This can be a lost opportunity. For older adults and individuals with diminished visual acuity, diminished cognition, and/or dexterity limitations, enabling the caregiver in the use of digital technology to provide support to the patient may be crucial in determining whether a program will be successful. There are also practical and ethical considerations when involving caregivers. Who gets alerts, who has permission to access information, and how do we monitor the burden on caregivers are some examples of concerns. The home environment is critical to realistic HF digitalization. If programs are available that allow caregivers to have optional portals, share reminders, or receive simple summaries, they may enhance adherence and reduce anxiety. Future research should include explicit assessments of caregiver experiences. Digital technologies can either reduce the burden of caregiving by enhancing communication, or increase the burden of caregiving by creating new technical responsibilities. (Vinter et al., 2026; Hon et al., 2026). Representative evidence and associated implementation implications are summarized in Table 1.

Table 1. Representative evidence and implementation implications for digital technologies in heart failure, 2022–2026.

Domain	Representative source	Key message	Implication for practice
Guidelines	ESC focused update, 2023	HF care continues to evolve around evidence-based treatment intensification and structured follow-up.	Digital tools should complement, not replace, guideline-directed care.
AI governance	AHA scientific statement, 2024	AI has broad potential in cardiovascular diagnosis and treatment but still requires robust validation and governance.	Adopt AI for defined use cases with oversight and outcome auditing.
Imaging AI	AHA cardiovascular imaging statement, 2024	AI may add value from image acquisition to interpretation and prognostic classification.	Best suited to workflow support and standardization.
Telemonitoring	Masotta et al., 2024	Telehealth and remote monitoring are associated with lower mortality and rehospitalization in HF.	Programs need organized review and follow-up response.
RPM components	De Lathauwer et al., 2025	Education, self-management support, and video communication strengthen RPM effectiveness.	Monitoring should be embedded in a care model, not used as a passive dashboard.
Wearables	Ginsburg et al., 2024	Wearables are entering clinical care, but validation, workflow integration, and intended use remain crucial.	Use trend data thoughtfully; distinguish consumer from medical-grade evidence.
Digital equity	Kim et al., 2024	Social determinants strongly shape access to and outcomes from digital cardiovascular interventions.	Equity assessment should be built into design, trial reporting, and implementation.
WHO policy	WHO digital health documents, 2024-2025	Digital health is a system enabler only if it remains person-centered, financed, and interoperable.	Infrastructure and reimbursement are as important as device innovation.

4. Discussion

4.1. Social implications and digital health equity

The biggest obstacle to successful digital heart failure (HF) care is that effectiveness and equity are intertwined. Models of care that result in better outcomes for those with greater levels of economic resources, education and literacy may fail those who are older, less digitally experienced, less financially stable and/or experience unstable access to care. Therefore, digital inclusion is not peripheral to the successful implementation of interventions. Digital inclusion is central to whether a digital HF intervention will work in real-world practice. Current research identifies digital HF as being comprised of much more than simply what tools we use and the outcomes that we measure. It is about access, representation, social support, trust, language and institutional design. (Kim et al., 2024; Nair et al., 2025; Powell-Wiley et al., 2025; World Health Organization Regional Office for Europe, 2026).

Most older adults living with heart failure are frail and also have multiple other chronic diseases, and many older adults live with vision loss, hearing loss, or other types of cognitive decline. Older adults' physical and/or mental changes all affect their ability to utilize a digital program. Small fonts, poor contrast (too light or dark), complex navigation processes, long and difficult onboarding, constant notifications, and instruction that is in a medical/technical style, may lead to less continued utilization. While older adults can certainly benefit from digital care, they generally prefer a relational model of care, meaning if the digital component is the only way the older adult receives follow-up, it will likely feel isolating. (Kim et al., 2024; Monlezun et al., 2025; World Health Organization Regional Office for Europe, 2026).

The larger systemic issues that contribute to inequities in digital health access, in some cases, are a result of how various patient populations can benefit (or fail to) in using remote health care. For example, rural patients could potentially benefit from less travel burden however they continue to face disadvantages from weaker broadband and less access to specialists. Additionally, low-income patients may experience difficulties with their smartphone, data plans, replacing a smartphone, and/or having a private area to conduct video telemedicine visits. Furthermore, individuals who have limited English proficiency will likely be excluded from digital HF care as long as all platforms, consent forms, and support services available to them are not provided in their native language. (World Health Organization, 2025; Powell-Wiley et al., 2025; Monlezun et al., 2025).

The use of AI models in the diagnosis of heart failure (HF) can produce additional layers of disparity. This disparity can occur in several ways. Bias can enter the process during data collection, label definition, choice of outcome measures or when the model is deployed. For example, if a model has been developed using tertiary center populations that have greater availability of advanced imaging techniques and therefore different co-morbidities; then the model will likely have poor calibration in under-resourced environments. Also, if healthcare utilization is chosen as a measure of disease severity then the model may encode previous access disparities into the model rather than biologic need. Women and other marginalized groups have traditionally suffered from delayed or missed diagnoses for HF. Therefore, there are serious concerns regarding potential for AI models to also suffer from these same issues. Algorithmic bias in HF models should not only be addressed by subgroup comparisons post deployment but should start with the development of the datasets through the inclusion of diverse patient recruitment methods, complete transparency regarding the model's performance and an independent third-party validation of the model. As stated previously, fairness should be a core aspect of model performance alongside discrimination and calibration. The requirements for institutions who plan to utilize AI tools for HF should include: a description of the population that was used to develop the model, a description of missing data patterns within the model, a report of subgroup performance for the model, and mechanisms for continuous monitoring of model performance. If an institution does not implement these safeguards, then they risk creating the very disparities that they claim to eliminate through the use of digital cardiology. (Armoundas et al., 2024; Kim et al., 2024; Alyacoub et al., 2025).

A frequently unspoken yet very significant social impact is the amount of clinician burden created by digital health care. If the number of messages and alerts increases, and there are no new personnel or workflow redesigns, the result may be more administrative work, less attention to the highest value tasks, and reduced clinician trust in the system. Therefore, evaluating digital care should include not only patient outcomes but also clinician workload, distribution of responsibility, and organizational justice. A program that appears efficient from the perspective of device-generated data may still be inequitable if it shifts hidden labor onto already strained teams. (Cajita et al., 2026; Jamieson et al., 2025; World Health Organization Regional Office for Europe, 2026).

Many cardiovascular studies using digital platforms continue to recruit participants that are generally motivated, technologically savvy and tied to academic health centers. This creates an evidence paradox: digital solutions are evaluated primarily by individuals least likely to face access barriers, while the main rationale for using them is to improve access for those most likely to experience barriers to traditional healthcare. Therefore, trial efficacy may provide an overly optimistic view of real-world effectiveness. A digital intervention for heart failure (HF) designed with equity in mind would require proactive recruitment from underserved clinics, provision of devices when needed, materials available in multiple languages, technical support, and reporting of onboarding and attrition as meaningful study outcomes. (Kim et al., 2024; Azizi et al., 2024; Vinter et al., 2026; Hon et al., 2026).

The way that we think about digital literacy in terms of how well a patient understands how to use technology for their health care is changing. Rather than viewing digital literacy as a background factor, healthcare systems should assess and support it much as they assess medication literacy or inhaler technique in other chronic diseases. A patient who cannot connect devices, understand alerts, or interpret messages may not be able to participate in monitoring-related treatment options. At the same time, digital literacy is not fixed:

many patients can successfully learn to use digital tools with proper training, repetition, and culturally sensitive support during onboarding. These findings suggest that supporting the use of technology by patients is part of the responsibilities associated with implementing new technologies. (Kim et al., 2024; World Health Organization, 2025; World Health Organization Regional Office for Europe, 2026).

A significant policy risk exists regarding the emergence of a "two-tier" model for digital cardiology. Advanced, well-equipped cardiology practices may be able to utilize implantable monitoring devices, data analysis systems, and AI-assisted workflow designs, while less well-equipped practices may face challenges providing even basic forms of remote follow-up. The continuation of this trend could widen disparities in access to specialists, continuity of care, and preventable hospitalizations. Therefore, ensuring that all patients have an equal opportunity to participate in digital heart failure (HF) treatment is not merely dependent upon the availability of technology, but rather on reimbursement policies, workforce models, purchasing, language support, and public infrastructure. As such, the implementation of digital HF treatment can be considered a question of health policy and social justice. (Monlezun et al., 2025; Nair et al., 2025; Powell-Wiley et al., 2025; World Health Organization Regional Office for Europe, 2026).

4.2. Ethical, regulatory, and implementation considerations

Strong, accountable, and transparent governance is necessary to protect the rights of patients who contribute data for use in digital health care delivery. These include, but are not limited to: using patient provided consent to make it clear what will happen with their data, limiting the ability to monetize patient contributed data for other than a patient's benefit, and creating clear lines of accountability for all institutions that collect and utilize patient contributed data. (World Health Organization, 2021; World Health Organization, 2025).

Many digital HF tools do not fail due to poor sensing, but rather because of inadequate system integration. Data arriving at a separate dashboard outside of the EHR generates resistance, and alerts without decision-support or triage logic add to the noise. Device data which does not fit into existing roles produces confusion about who will respond and how quickly. Recent reviews emphasize that the next major barrier is not proof that remote monitoring works, but development of care models that allow it to be sustainable. As such, interoperability should be viewed as a clinical quality issue, not just an IT preference. (Cajita et al., 2026; World Health Organization, 2021; World Health Organization, 2025).

The extent to which digital HF can be scaled for care delivery is contingent upon reimbursement structures. If technologies require intensive monitoring time, setup, patient education, and clinical review, then those technologies will not be able to scale if these efforts are not funded. Value assessments should include both hospitalization reductions and improvements in access, patient-centered convenience, reduced travel burden, and caregiver benefits. A rational value structure should correlate with the technology's intensity, the patient's risk and the expected gain. (Masotta et al., 2024; Cajita et al., 2026; World Health Organization Regional Office for Europe, 2026).

The pace of development of many digital interventions typically outpaces the traditional therapeutic interventions they are intended to enhance, thereby creating an apparent contradiction between the need for rapid development and rigorous validation of efficacy. Although not all apps and wearables require large-scale randomized trials to validate their technical capabilities, applications that could potentially affect diagnosis, treatment, or resource allocation will require much more rigorous validation. An appropriate hierarchy of evidence for digital tools used in heart failure care might include technical validation, clinical validation in the target population, evaluation of workflow effects, analysis of subgroup fairness, and evidence related to practical implementation. (Armoundas et al., 2024; Hanneman et al., 2024; Ginsburg et al., 2024).

Traditional medical devices generally evolve at a slower rate than traditional software. Adaptive AI systems add another layer of complexity since their performance may change over time as populations, practice patterns and data sources evolve. Therefore, regulatory oversight will need to consider not only original validation, but also ongoing post deployment monitoring. A reasonable governance framework should include documentation of intended use, external validation, planned changes to the system, audit trail capabilities and the ability to identify and track subgroups whose outcomes may degrade over time. This is of particular concern if the algorithm is embedded into standard clinical software, which may make it difficult to determine when a user is relying upon an AI-assisted recommendation versus their own judgment. (Armoundas et al., 2024; World Health Organization, 2021; World Health Organization, 2025).

When considering how digital HF tools work, interface design will help determine if predictions are used as action. Poor dashboard organization, unclear visualization, too many clicks, or ambiguous labeling could hinder effective utilization of even the best performing systems. User experience therefore plays a role in determining clinical effectiveness. Clinicians require concise summary information, trend visualization, and prioritized abnormalities; patients require clear and simple interfaces; caregivers require shared responsibility and accessible escalation options. Future studies should report interface and user-experience aspects more systematically, as replicating the technical aspects of a system without replicating its design is generally insufficient. (Ginsburg et al., 2024; Jamieson et al., 2025). Priority implementation principles derived from this literature are summarized in Table 2.

Table 2. Priority principles for equitable implementation of digital heart failure care.

Principle	Operational implication
Match technology intensity to clinical risk	Use basic telehealth and simple home monitoring for broad populations, while reserving advanced implantable or AI-intensive pathways for selected high-risk patients.
Provide onboarding and technical support	Treat setup, training, and troubleshooting as part of care delivery rather than assuming pre-existing digital competence.
Require external validation and subgroup reporting	Assess AI tools across sex, age, language, and socially vulnerable populations before large-scale adoption.
Integrate remote data into workflow	Define ownership, escalation rules, and reimbursement for data review so that information leads to timely clinical action.
Design for older and frail populations	Use multilingual, low-burden, caregiver-aware interfaces and simplified engagement pathways.
Measure equity-sensitive outcomes	Track enrollment, onboarding completion, sustained use, hospitalization, quality of life, and patient burden across subgroups.

4.3. Future directions

The trend toward digitalizing heart failure (HF) information has an obvious trajectory. Artificial intelligence (AI) is likely to become increasingly embedded in the interpretation of electrocardiogram (ECG) data, the analysis of medical images, and assessments of patient risk. Wearable devices are continuing to move from wellness tracking toward clinically relevant biosensing, while remote monitoring is moving away from individualized measurement of discrete parameters to integrated, dynamic care pathways. Conversational interfaces and digital assistants may eventually provide symptom triage, educational support and adherence support, although this area remains nascent. (Zhang et al., 2026; Gaona et al., 2024).

The biggest barrier to progress, however, isn’t technological sophistication - it's the fair application of technology to all. Future randomized trials should therefore include a large proportion of those previously excluded from digital health, such as the oldest old, rural patients, individuals with limited English proficiency and others who are socioeconomically disadvantaged. In addition to subgroup performance, future trials should also report onboarding rates, sustained engagement, and perceived digital burden by subgroup. (Kim et al., 2024; Vinter et al., 2026; Hon et al., 2026).

A second priority is to integrate patient self-reporting and lived experience into digital heart failure (HF) systems. Passive physiologic monitoring provides no information about symptoms, burdens of treatment, or quality of life. The next generation of powerful platforms will likely combine passive sensing with simple and low burden patient input and a direct, clear clinical response. As in other public health areas, simple devices that can be made widely available and used comprehensively may produce greater population health benefits than highly complex ones which can only be used by a few. (Tunis et al., 2024; Noci et al., 2025; Nair et al., 2025).

A tiered, risk-based model may be the most effective way to describe what the future holds. At the population level, AI-enhanced ECGs and digital risk scores may support early detection of occult ventricular dysfunction and referral for echocardiography. Telemedicine and basic remote monitoring may assist in maintaining continuity of care, reinforcing self-care, and monitoring treatment response for patients already receiving treatment. For patients at high risk of severe disease or recurrent decompensation, implantable hemodynamic monitors and dense multiparameter surveillance may be used. A tiered system has the advantage of pairing the appropriate level of technology with the appropriate level of clinical need while also addressing equity when basic digital access is viewed as an essential part of standard care rather than an optional enhancement. Broad, low-cost digital services combined with selective advanced monitoring may therefore provide a more equitable and sustainable option than indiscriminate use of expensive technologies. (Desai et al., 2026; Bayes-Genis et al., 2025; Teleanu et al., 2025).

Research priorities arise from the current literature on digital tools used for remote monitoring of patients with heart failure. Priorities include conducting pragmatic randomized and implementation trials in different healthcare environments; standardizing outcomes beyond hospitalization and mortality to include treatment intensification, quality of life, burden of alerts, onboarding success, sustained engagement, and subgroup equity; improving interoperability and clarifying who will respond to incoming data; and continuing to explore multimodal systems that combine physiological data, symptom reports, and AI-based trend analysis. Future investigations should also examine whether remote monitoring allows clinicians to identify worsening heart failure early enough to change management in ways that matter to patients and health systems. (Cajita et al., 2026; Masotta et al., 2024; Teleanu et al., 2025).

4.4. Practical implications for clinicians and health systems

Clinical use of digital HF tools as described in this article means they need to be used thoughtfully and with purpose, not just because they're available. Clinicians might find it valuable to consider using AI tools to screen patients for risk (or even to identify who's at high risk) when they have been validated by someone outside their own practice and when there are specific treatment options based on the patient's risk level. It would likely be easier to defend telehealth and remote monitoring if there is a clearly established multidisciplinary team with a response plan to address any issues that arise, as well as a well-defined target population. (McDonagh et al., 2023; Masotta et al., 2024).

The message to health systems is a little different. Investment in digital HF care must go beyond just devices (on-boarding, multiple languages, staffing, etc.) to include an infrastructure of interoperability, evaluation, governance and ultimately the ability to measure success based on both adoption rate and if digitally enabled HF care actually reaches those at highest risk for HF who lack access to traditional specialist follow up. Therefore, while a program may have all the technical sophistication of a "high tech" program, it could still represent a weak commitment to cardiovascular policy if it does not provide some degree of access to the greatest numbers of people at the highest risk. Health systems will require implementation models that are designed to ensure adequate reimbursement, sufficient levels of digital literacy among caregivers as well as patients, inclusion of caregivers in decision making processes regarding HF management and that they are held accountable for ensuring equal access to HF care. (McDonagh et al., 2023; Kim et al., 2024; Cajita et al., 2026; World Health Organization Regional Office for Europe, 2026).

5. Conclusions

Digital technologies have had a profound effect on how we provide heart failure (HF) care; however, their most significant contributions will come not from innovation alone. The current body of literature (2022-2026) supports that artificial intelligence (AI), telemedicine, wearable monitoring, and implantable hemodynamic sensing may enhance diagnostic capabilities, risk stratification, longitudinal surveillance, and clinical outcomes in certain patient populations. Telemedicine appears most effective when combined with structured care pathways, education, self-management strategies, and timely human response. While there is considerable potential for AI use in ECG-based screening, imaging, and phenotyping, AI currently exists in a transitional phase where external validation, interpretability, and implementation science are as important as model performance.

Simultaneously, many studies have cautioned that the digital revolution in healthcare could exacerbate existing health inequities if not developed with consideration of access, literacy, language, age, workflow, and fairness. Given that HF disproportionately affects the elderly and those who are socially vulnerable, equitable design is essential. Therefore, digital cardiology must be evaluated based on two standards: does it lead to improved patient outcomes, and does it do so equitably? The future of HF digital care should be hybrid, person-centered, evidence-based, and explicitly equity-oriented, with technology serving as an enabling mechanism for smarter, earlier, and more accountable cardiovascular care.

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REFERENCES

1. Alyacoub, R. (2025). Artificial intelligence in heart failure: A comprehensive literature review. *Cardiology Journal, 32*(6), 655–665. https://doi.org/10.5603/cj.104365
2. Armoundas, A. A., Narayan, S. M., Arnett, D. K., Spector-Bagdady, K., Bennett, D. A., Celi, L. A., Friedman, P. A., Gollob, M. H., Hall, J. L., Kwitek, A. E., Lett, E., Menon, B. K., Sheehan, K. A., Al-Zaiti, S. S., & American Heart Association Institute for Precision Cardiovascular Medicine Committee. (2024). Use of artificial intelligence in improving outcomes in heart disease: A scientific statement from the American Heart Association. *Circulation, 149*(14), e1028–e1050. https://doi.org/10.1161/CIR.0000000000001201
3. Azizi, Z., Broadwin, C., Islam, S., Schenk, J., Din, N., Funes Hernandez, M., Wang, P., Longenecker, C. T., Rodriguez, F., & Sandhu, A. T. (2024). Digital health interventions for heart failure management in underserved rural areas of the United States: A systematic review of randomized trials. *Journal of the American Heart Association, 13*(2), e030956. https://doi.org/10.1161/JAHA.123.030956
4. Bayes-Genis, A., Pagnesi, M., Codina, P., Abraham, W. T., Amir, O., de Boer, R. A., Brugts, J. J., Chioncel, O., Gustafsson, F., Lindenfeld, J., Mullens, W., Petrie, M. C., Rosano, G., & Metra, M. (2025). Remote pulmonary artery pressure-guided management of patients with heart failure: A clinical consensus statement of the Heart Failure Association (HFA) of the ESC. *European Journal of Heart Failure, 27*(9), 1644–1657. https://doi.org/10.1002/ejhf.3619
5. Cajita, M., Peters, L., Rao, V. N., Kitsiou, S., Leigh, J. W., Kansal, M. M., Vuckovic, K. M., Reilly, C. M., Bozkurt, B., Fedson, S., & DeVore, A. D. (2026). Integrated health technologies in heart failure: A scientific statement from the Heart Failure Society of America and the American Association of Heart Failure Nurses. *Heart & Lung*. Advance online publication. https://doi.org/10.1016/j.hrtlng.2025.11.020
6. De Lathauwer, I. L. J., Nieuwenhuys, W. W., Hafkamp, F., Kuepers, B. G. M., Brunner-La Rocca, H.-P., & van Empel, V. P. M. (2025). Remote patient monitoring in heart failure: A comprehensive meta-analysis of effective programme components for hospitalization and mortality reduction. *European Journal of Heart Failure, 27*(9), 1670–1685. https://doi.org/10.1002/ejhf.3568
7. Desai, A. S., Pandey, A., Suratekar, R., Ahmad, F. S., Alger, H. M., Anto, A. G., Nujum, S. G., Lopez-Jimenez, F., Oh, J. K., Asfahan, S., Narasimha, S., Reddy, S. N., Kaligounder, L., Ciga, M., Awasthi, S., Butler, J., Shah, S. H., & Shah, S. J. (2026). Predicting heart failure from 12-lead ECGs using AI: A HeartShare/AMP-HF pooled cohort analysis. *Journal of the American College of Cardiology, 87*(8), 990–1005. https://doi.org/10.1016/j.jacc.2025.10.065
8. Dhingra, L. S., Aminorroaya, A., Pedroso, A. F., Khunte, A., Sangha, V., McIntyre, D., Chow, C. K., Asselbergs, F. W., Brant, L. C. C., Barreto, S. M., Ribeiro, A. L. P., Krumholz, H. M., Oikonomou, E. K., & Khera, R. (2025). Artificial intelligence-enabled prediction of heart failure risk from single-lead electrocardiograms. *JAMA Cardiology, 10*(6), 574–584. https://doi.org/10.1001/jamacardio.2025.0492
9. Gaona, G. A., Kassamali, A. A., Isakadze, N., & Martin, S. S. (2024). Harnessing wearables and digital technologies to decode the cardiovascular exposome. *Methodist DeBakey Cardiovascular Journal, 20*(5), 59–70. https://doi.org/10.14797/mdcvj.1459
10. Ginsburg, G. S., Picard, R. W., & Friend, S. H. (2024). Key issues as wearable digital health technologies enter clinical care. *New England Journal of Medicine, 390*(12), 1118–1127. https://doi.org/10.1056/NEJMra2307160
11. Hanneman, K., Playford, D., Dey, D., van Assen, M., Mastrodicasa, D., Cook, T. S., Gichoya, J. W., Williamson, E. E., & Rubin, G. D. (2024). Value creation through artificial intelligence and cardiovascular imaging: A scientific statement from the American Heart Association. *Circulation, 149*(6), e296–e311. https://doi.org/10.1161/CIR.0000000000001202
12. Hon, J. J., & Carr-White, G. (2026). The digital divide in cardiovascular care: Who gets left behind? *European Heart Journal – Digital Health, 7*(2), ztag011. https://doi.org/10.1093/ehjdh/ztag011
13. Jamieson, A., Chico, T. J. A., Jones, S., Chaturvedi, N., Hughes, A. D., & Orini, M. (2025). A guide to consumer-grade wearables in cardiovascular clinical care and population health for non-experts. *npj Cardiovascular Health, 2*(1), Article 44. https://doi.org/10.1038/s44325-025-00082-6

14. Kim, D. S., Eltahir, A. A., Ngo, S., & Rodriguez, F. (2024). Bridging the gap: How accounting for social determinants of health can improve digital health equity in cardiovascular medicine. *Current Atherosclerosis Reports, 27*(1), Article 9. https://doi.org/10.1007/s11883-024-01249-9
15. Masotta, V., Dante, A., Caponnetto, V., Marcotullio, A., Ferraiuolo, F., Bertocchi, L., D'Eramo, C., Tontodonati, M., & Martone, D. (2024). Telehealth care and remote monitoring strategies in heart failure patients: A systematic review and meta-analysis. *Heart & Lung, 64*, 149–167. https://doi.org/10.1016/j.hrtlng.2024.01.003
16. Masterson Creber, R., Hickey, K. T., Maurer, M. S., Breathett, K., Choi, E., Colon-Emeric, C., Davis, L. L., Hall, J. L., Heisler, M., Jaarsma, T., Kitzman, D. W., Rich, M. W., Sterling, M. R., Warraich, H. J., Wessler, B. S., White-Williams, C., & Ibrahim, N. E. (2023). Telehealth and health equity in older adults with heart failure: A scientific statement from the American Heart Association. *Circulation: Cardiovascular Quality and Outcomes, 16*(11), e000123. https://doi.org/10.1161/HCQ.0000000000000123
17. McDonagh, T. A., Metra, M., Adamo, M., Gardner, R. S., Baumbach, A., Böhm, M., Burri, H., Butler, J., Čelutkienė, J., Chioncel, O., Cleland, J. G. F., Coats, A. J. S., Crespo-Leiro, M. G., Farmakis, D., Gilard, M., Heymans, S., Hoes, A. W., Jaarsma, T., Jankowska, E. A., . . . ESC Scientific Document Group. (2023). 2023 focused update of the 2021 ESC guidelines for the diagnosis and treatment of acute and chronic heart failure. *European Heart Journal, 44*(37), 3627–3639. https://doi.org/10.1093/eurheartj/ehad195
18. Medhi, D., Kamidi, S. R., Mamatha Sree, K. P., Shaikh, S., Rasheed, S., Murichathil, A. H. T., & Nazir, Z. (2024). Artificial intelligence and its role in diagnosing heart failure: A narrative review. *Cureus, 16*(5), e59661. https://doi.org/10.7759/cureus.59661
19. Monlezun, D. J., Omutoko, L., Oduor, P., Kokonya, D., Rayel, J., Sotomayor, C., Girault, M. I., De Los Rios Uriarte, M. E., Sinyavskiy, O., Aksamit, T., Dugani, S. B., Garcia, A., & Gallagher, C. (2025). Digitalization of health care in low- and middle-income countries. *Bulletin of the World Health Organization, 103*(2), 148–154. https://doi.org/10.2471/BLT.24.291643
20. Myhre, P. L., Tromp, J., Ouwerkerk, W., Ting, D. S. W., Docherty, K. F., Gibson, C. M., & Lam, C. S. P. (2024). Digital tools in heart failure: Addressing unmet needs. *The Lancet Digital Health, 6*(10), e755–e766. https://doi.org/10.1016/S2589-7500(24)00158-4
21. Nair, P., Dai, M., Patel, D. A., Pearlman, K., & Shah, S. D. (2025). Equity by design—Using digital technology to overcome cardiovascular health disparities. *Current Cardiology Reports, 27*(1), Article 157. https://doi.org/10.1007/s11886-025-02319-3
22. Nazir, A., Nazir, A., Jamal, M. S. W., Sadiq, S. U. R., Aman, S., Mustapha, M. J., Lawal, S. O., AbdulKareem, M. O., & Bamigbola, M. F. (2025). Wearable technology and its potential role in cardiovascular health monitoring and disease management. *Health Science Reports, 8*(11), e71486. https://doi.org/10.1002/hsr2.71486
23. Noci, F., Capodici, A., Nuti, S., Passino, C., Emdin, M., & Giannoni, A. (2025). Wearable technologies to predict and prevent heart failure hospitalizations: A systematic review. *European Heart Journal – Digital Health, 6*(5), 868–877. https://doi.org/10.1093/ehjdh/ztaf079
24. Pierre-Jean, M., Marut, B., Curtis, E., Leclercq, C., Samset, E., Hernandez, A. F., Donal, E., & Omar, A. M. S. (2024). Phenotyping of heart failure with preserved ejection fraction using electronic health records and echocardiography. *European Heart Journal Open, 4*(1), oead133. https://doi.org/10.1093/ehjopen/oead133
25. Powell-Wiley, T. M., Brewer, L. C., Burke, L. E., Hernandez, R., Landsbaugh Kaar, J., Kepper, M., Kline, C. E., Lopez, K. N., Roberson, S., Spees, C. K., & Jerome, G. J. (2025). Role of technology in promoting heart healthy behavior change to increase equity in optimal cardiovascular health: A scientific statement from the American Heart Association. *Circulation, 151*(18), e972–e985. https://doi.org/10.1161/CIR.0000000000001314
26. Sau, A., Pastika, L., Sieliwonczyk, E., Patlatzoglou, K., Ribeiro, A. H., McGurk, K. A., Zeidaabadi, B., Zhang, H., Macierzanka, K., Mandic, D., Sabino, E., Giatti, L., Barreto, S. M., do Valle Camelo, L., Tzoulaki, I., O'Regan, D. P., Peters, N. S., Ware, J. S., Ribeiro, A. L. P., . . . Ng, F. S. (2024). Artificial intelligence-enabled electrocardiogram for mortality and cardiovascular risk estimation: A model development and validation study. *The Lancet Digital Health, 6*(11), e791–e802. https://doi.org/10.1016/S2589-7500(24)00172-9
27. Scagliusi, S. F., Gimenez-Miranda, L., Perez-Garcia, P., Olmo-Fernandez, A., Huertas-Sanchez, G., Medrano-Ortega, F. J., & Yufera-Garcia, A. (2024). Wearable devices based on bioimpedance test in heart failure: Design issues. *Reviews in Cardiovascular Medicine, 25*(9), Article 320. https://doi.org/10.31083/j.rcm2509320
28. Teleanu, I. C., Bejan, G. C., Poiana, I. R., Mirsu-Paun, A., Dumitrescu, S. I., & Stanescu, A. M. A. (2025). Remote monitoring of patients with heart failure: Characteristics of effective programs and implementation strategies. *Vascular Health and Risk Management, 21*, 489–503. https://doi.org/10.2147/VHRM.S521952
29. Tolu-Akinnawo, O., Akhtar, N., Zalavadia, N., & Guglin, M. (2025). CardioMEMS heart failure system: An up-to-date review. *Cureus, 17*(1), e77816. https://doi.org/10.7759/cureus.77816
30. Tunis, R., West, E., Clifford, N., Horner, S., & Radhakrishnan, K. (2024). Leveraging digital health technologies in heart failure self-care interventions to improve health equity. *Nursing Outlook, 72*(5), 102225. https://doi.org/10.1016/j.outlook.2024.102225

31. Vinter, N., Elmegaard, M., Køber, L., & Schou, M. (2026). Inequity in access to and use of digital health technologies in routine heart failure care: Protocol for a scoping review. *JMIR Research Protocols, 15*, e81949. https://doi.org/10.2196/81949
32. World Health Organization. (2021). *Global strategy on digital health 2020–2025*. https://www.who.int/publications/i/item/9789240020924
33. World Health Organization. (2025). *Global repository on national digital health strategies*. Retrieved March 17, 2026, from https://www.who.int/teams/digital-health-and-innovation/global-repository-on-national-digital-health-strategies
34. World Health Organization Regional Office for Europe. (2026). *Building financing pathways for digital health technologies in the WHO European Region*. https://iris.who.int/server/api/core/bitstreams/d1d35fcb-fb8c-4e1c-adb2-b11cd6f312b5/content
35. Yi, J.-E., & Cho, J. S. (2026). Artificial intelligence in HFpEF: Diagnosis, prognosis, and management strategies. *Journal of Cardiology, 87*(2), 113–120. https://doi.org/10.1016/j.jjcc.2025.08.018
36. Zhang, C., Yang, Z., & Tang, Y.-D. (2026). Integrating multimodal intelligence in heart failure: AI-driven risk prediction, precision diagnosis, phenotyping, personalized treatment, and prognosis. *Chinese Medical Journal, 139*(5), 672–688. https://doi.org/10.1097/CM9.0000000000004000