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Artificial Intelligence in Heart Failure: Early Detection, Phenotyping, and Prognostic Modeling

REVIEW

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ABSTRACT

This review examines the role of artificial intelligence (AI) across the heart failure (HF) continuum, with particular emphasis on patient identification and early recognition, AI-enabled electrocardiography and echocardiography, etiologic and phenotypic classification, electronic health record-based staging and risk prediction, advanced HF identification, continuous monitoring, treatment optimization, and emerging applications of agentic AI.

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INTRODUCTION

Heart Failure (HF) remains a major burden of cardiovascular (CV) diseases in the United States, affecting approximately 7.7 million Americans older than 20 years of age.[1] In 2023, HF accounted for approximately 9.8% of CV deaths and was mentioned on more than 450,000 death certificates.[1,2] Despite major advances in medical- and device-based therapies, mortality due to HF remains high.

With the growing burden of heart failure, it is even more essential to prioritize early recognition, more precise risk stratification, and individualized treatment. Delayed identification postpones the initiation of disease modifying therapies and contributes to progression of structural and functional cardiac abnormalities. However, the clinical trajectory towards HF is rarely captured by a single measurement. Relevant information may be distributed across electrocardiograms (ECGs), echocardiograms, laboratory testing, vital signs, comorbidities, medications, healthcare utilization, and longitudinal clinical notes.[3]

Artificial intelligence (AI) is emerging as a tool that can integrate this data, identifying patterns within high-dimensional and longitudinal clinical data that may not be apparent through conventional assessment alone.[4] Rather than representing a single diagnostic application, AI may be integrated across the HF continuum, from patient identification and diagnosis to phenotyping, risk stratification, treatment optimization, and recognition of advanced disease.[4] This review examines the role of AI across the HF continuum, with particular emphasis on AI-enabled ECG and echocardiography, etiologic and phenotypic classification, electronic health record (EHR)-based staging and risk prediction, advanced HF identification, treatment optimization, and emerging applications of agentic AI.

METHODS

SEARCH STRATEGY

A narrative literature search was conducted across PubMed, Google Scholar, Embase, and MEDLINE to identify relevant literature examining the application of AI in HF. These sources were selected for their broad coverage of clinical literature, including peer-reviewed research and review articles relevant to heart failure care and emerging applications of AI.

The search strategy incorporated a combination of Medical Subject Headings (MeSH) and free-text keywords related to both artificial intelligence and heart failure. AI-related terms included artificial intelligence, machine learning, deep learning, natural language processing, large language models, and related computational approaches. Heart failure-related terminology included heart failure, cardiac failure, heart failure with preserved ejection fraction (HFpEF), heart failure with reduced ejection fraction (HFrEF), and heart failure with mildly reduced ejection fraction. Additional terms were added to incorporate various applications of AI, including recognition, identification, detection, phenotyping, classification, risk stratification, management, monitoring, and patient education. The finalized PubMed search strategy is presented below.

ARTICLE INCLUSION CRITERIA

Articles were considered for inclusion if they were published from 2020 onwards and if the topics dealt with AI being incorporated into HF care. Those considered emphasized modern developments in AI and their application to HF care. Studies were considered relevant if they examined the use of AI in HF recognition, identification, phenotyping, classification, diagnosis, risk stratification, monitoring, or management. Literature addressing the use of AI to support treatment decisions, patient education, or other aspects of HF care was also considered.

The initial search identified 7,043 records. Following preliminary screening for relevance to the scope of the review, 255 articles were retained.

DATA COLLECTION

The 255 articles identified during initial screening underwent further review to determine their relevance to the objectives of the review. Full-text articles were examined to see whether they addressed the application of AI to HF recognition, characterization, clinical management, or patient-centered care in detail.

Articles that were outside the primary scope of the review were excluded in the final narrative synthesis. Duplicate publications, external validation studies that did not substantially expand upon the primary findings, and other articles that did not provide sufficient information for the themes examined here were also excluded from the final synthesis. Following this process, articles relevant to the review objectives were included in the final narrative synthesis.

DATA SYNTHESIS

The selected articles were synthesized using a narrative approach. Data from the selected articles was organized according to common themes of AI in HF. Articles that mainly discussed how AI may contribute to the recognition and characterization of HF, support clinical decision-making and treatment, enhance longitudinal monitoring, and improve patient understanding and engagement were looked at in more detail.

Because this study was designed as a narrative rather than a systematic review, a formal risk of bias or methodological quality assessment was not done. Instead, emphasis was placed on peer-reviewed literature that was relevant to the review objectives, with findings interpreted in the context of study design, clinical applicability, consistency with the broader literature, and limitations reported by the authors.

NINE THEMES IDENTIFIED IN LITERATURE

Nine major themes were identified from the literature: patient identification and early recognition; automation at the point of care; phenotyping and etiologic classification; staging and risk stratification; management and treatment optimization; advanced heart failure stratification; continuous monitoring and outcomes; patient engagement and clinical impact; and clinical implementation, limitations, and future directions. Findings within each theme were integrated to highlight areas of progress, emerging applications, limitations of existing technologies and evidence, and opportunities for future investigation.

1. PATIENT IDENTIFICATION AND EARLY RECOGNITION

An important application of AI is patient identification. AI-enabled ECG has advanced in recent years. Deep-learning algorithms applied to routine ECGs have shown the ability to identify occult left ventricular (LV) systolic dysfunction and patients at increased risk of developing HF[5,6] In a pragmatic randomized trial involving more than 22,000 patients, use of an AI-enabled ECG algorithm increased the diagnosis of previously unrecognized low LV ejection fraction (LVEF) in routine clinical practice.[7]

AI-ECG models have also been investigated for detecting HFpEF, suggesting that information relevant to both systolic and diastolic dysfunction may be encoded within electrical signals that are not readily discernible by conventional ECG interpretation.[8-10] Such approaches may allow the widely available and relatively inexpensive ECG to function not only as a diagnostic test for electrical abnormalities but also as a screening and triage tool for structural and functional heart disease.[8,9,11]

AI-enabled ECG provides a particularly scalable approach because ECGs are inexpensive, widely available, and routinely obtained in both ambulatory and acute-care settings. Algorithms capable of identifying reduced LVEF, HFpEF, or future HF risk could serve as an initial screening layer that identifies individuals who warrant echocardiography or additional cardiovascular evaluation.[5-12] Rather than replacing echocardiography, AI-ECG may improve selection of patients for imaging. This concept may be particularly valuable in primary care and resource-limited environments where universal echocardiographic screening is impractical.

AI can identify high-risk or potentially undiagnosed HF patients by analyzing routinely collected EHR data, including diagnoses, medications, laboratory values, prior hospitalizations, symptoms, and clinical documentation.[13] EHR-based case-finding models may help prioritize patients who require further assessment and reduce the number of records that clinicians must manually review. These tools could support nurses, primary-care clinicians, and other members of the care team by flagging patients for targeted evaluation, confirmatory testing, or specialist referral rather than relying solely on recognition during an individual clinical encounter.[13,14]

Thus, AI-based patient identification may allow HF care to begin before a patient presents with overt decompensation, particularly when subtle abnormalities are already present within routinely collected clinical data.[6,8,10]

Selected studies showing the potential application of AI for early identification and recognition of HF are summarized in Table 1.[15-18]

2. AUTOMATION AT THE POINT OF CARE

Recent advances in AI have significantly expanded what's possible in echocardiography, enhancing image acquisition, interpretation, and quantitative analysis. Deep-learning models can automate measurements of chamber size, left ventricular volumes, and ejection fraction with high reproducibility, while newer models can integrate two-dimensional and Doppler data to automate assessment of diastolic function.[19-22]

AI may also assist image acquisition itself. Systems that provide real-time guidance can enable less-experienced operators to obtain diagnostically useful cardiac ultrasound images, potentially extending point-of-care echocardiography to settings where expert sonographers are not readily available.[23] These capabilities could improve efficiency while reducing interobserver variability and expanding access to cardiovascular imaging.[19,23]

Once patients are selected for imaging, AI-assisted echocardiography could further reduce barriers to recognition. Automated chamber quantification, LVEF assessment, and diastolic function grading may improve reproducibility and decrease the time required for interpretation.[19-21] AI-guided acquisition may also enable clinicians with limited ultrasonography experience to obtain clinically interpretable point-of-care studies.[23]

The combination of AI-ECG screening and AI-assisted point-of-care echocardiography may create a practical

SOURCE	INTERVENTION DETAILS	ASSESSMENT
Guo et al., 2025	Developed and validated a convolutional neural network (CNN) model using a single lead ECG and phonocardiogram signals recorded by a digital stethoscope to detect reduced EF.	Assessed diagnostic performance in 2,960 adults. The model achieved an AUC of 0.85, with 77.5% sensitivity and 78.3% specificity for detecting LVEF ≤ 40%.
Dhingra et al., 2025	Applied a noise adapted AI-ECG model to Lead I signals extracted from 12 lead ECGs to predict incident HF across three multinational cohorts.	Assessed incident HF prediction and compared performance with clinical risk scores. The model achieved C statistics of 0.723-0.828 and improved risk discrimination when combined with clinical risk scores.
Desai et al., 2026	Applied waveform-based ECG-AI models for low ejection fraction and diastolic dysfunction to 12-lead ECGs from participants without prevalent HF/CVD. ECG-AI was evaluated and combined with PREVENT-HF.	Assessed incident HF prediction at 1-, 3-, 5-, and 10-year horizons, reclassification, and clinical utility compared with PREVENT-HF. ECG-AI added predictive information beyond clinical risk assessment.
Karabayir et al., 2026	Previously validated deep-learning ECG-AI model analyzed a 12-lead ECG per patient to estimate future HFpEF risk across prediction windows from 6 months to 10 years.	Assessed future HFpEF diagnosis, discrimination across prediction horizons, compared with H2FPEF score, and risk stratification. ECG-AI outperformed H2FPEF by 0.06-0.07 AUC.
Shropshire et al., 2026	Applied a previously validated AI-ECG algorithm to 12 lead ECGs from patients with AF to predict incident HF with EF < 50%.	Assessed HF risk prediction in 2,569 patients. The highest AI-ECG risk tertile was associated with increased HF risk (HR 3.50; 95% CI, 2.51-4.87), with improved discrimination when combined with clinical risk factors.

Table 1 Selected studies demonstrating artificial intelligence-based approaches for early identification and recognition of heart failure. AI: artificial intelligence; ML: machine learning; AF: atrial fibrillation; HF: heart failure; ECG: electrocardiography; CVD: cardiovascular disease; AUC: area under the curve; HFpEF: heart failure with preserved ejection fraction; LVEF: left ventricular ejection fraction; EF: ejection fraction

pathway in which initial patient identification is followed by rapid targeted assessment of cardiac structure and function.[19,23,24] Figure 1 illustrates the application of AI in automating clinical processes at the point of care.

3. PHENOTYPING AND ETIOLOGIC CLASSIFICATION

Beyond recognition of HF itself, AI may help in identifying the underlying disease phenotype and etiology. HF comprises a heterogeneous group of syndromes rather than a single disease, and patients with similar symptoms or LVEF may have substantially different underlying pathophysiology.[25-27]

ECG- and echocardiography-based algorithms have been developed to detect conditions such as hypertrophic cardiomyopathy and cardiac amyloidosis, including disease signatures that can precede conventional clinical recognition.[28,29] AI models applied to ECG and imaging have also shown encouraging performance for differentiation of cardiac amyloidosis from other causes of increased ventricular wall thickness.[29]

Multimodal models combining ECG, imaging, laboratory, and clinical information may distinguish phenotypically overlapping conditions and help direct patients toward confirmatory testing.[30-33] Future multimodal models incorporating ECG, echocardiography, cardiac magnetic resonance, biomarkers, genetics, and longitudinal clinical information may allow etiologic classification to occur earlier in the diagnostic pathway.[27,30]

This represents an important transition from using AI simply to determine whether HF is present to using AI to determine why HF has developed and which phenotype may be driving the clinical presentation.

4. STAGING AND RISK STRATIFICATION

AI may also help define where an individual patient lies along the HF continuum. Machine-learning models can integrate laboratory values, comorbidities, medications, imaging findings, and other EHR data to estimate the risk of incident HF, hospitalization, mortality, or clinical deterioration rather than relying on single parameters such as LVEF.[34-37]

This longitudinal risk assessment increases the possibility of identifying patients with Stage A or B HF before symptoms develop, differentiating patients with stable Stage C disease from those with worsening trajectories, and identifying patients approaching advanced Stage D HF who may benefit from earlier referral.[38,39]

Disease staging represents another important area in which AI may add value. Contemporary HF staging recognizes a continuum from risk factors without structural disease to advanced symptomatic HF, but clinical staging is often performed cross-sectionally.[38] AI could provide a more dynamic assessment by integrating changing clinical variables over time.[34-36] A patient with preserved LVEF, for example, may simultaneously demonstrate worsening diastolic function, increasing natriuretic peptide concentrations, recurrent congestion, worsening renal

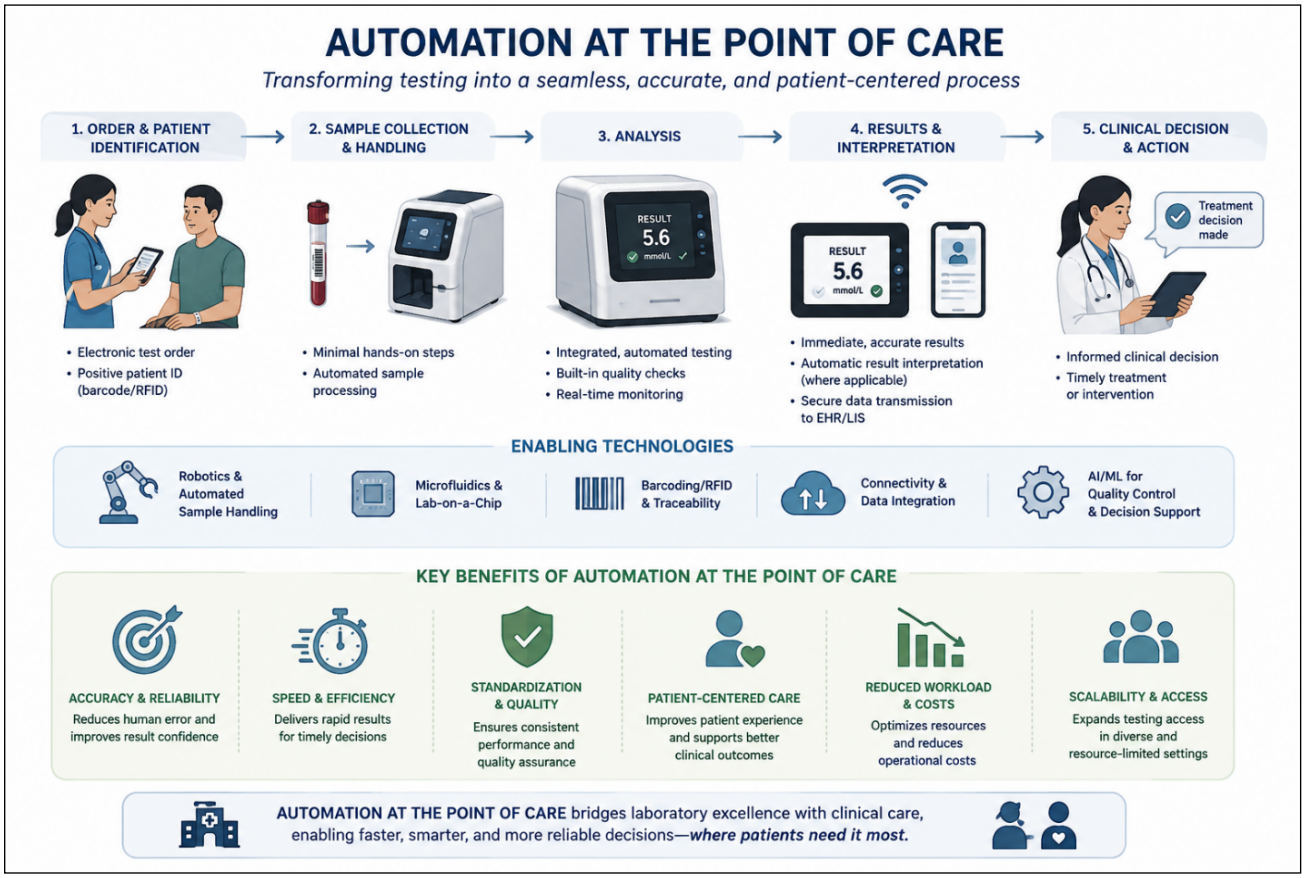


Figure 1 Conceptual framework illustrating how artificial intelligence may support automation at the point of care in heart failure. Figure created with the assistance of ChatGPT and verified. EHR: electronic health record; LIS: laboratory information system; RFID: radiofrequency identification; AI: artificial intelligence; ML: machine learning

function, and escalating diuretic requirements. Evaluating these variables together may identify a deteriorating trajectory that is not adequately represented by LVEF alone.[35,36,38]

The value of AI in staging may lie not only in assigning a patient to a particular HF stage but also in recognizing movement from one stage or risk state to another.

5. MANAGEMENT AND TREATMENT OPTIMIZATION

The next step after recognition and risk prediction is to translate these findings into action. Guideline-directed medical therapy (GDMT) remains underused in clinical practice. Digital clinical decision-support systems can identify eligible patients, detect therapeutic gaps, and provide patient-specific recommendations for care.[40,41]

Randomized studies of EHR-based decision support have shown that appropriately designed alerts can increase initiation of HF therapies, although effectiveness varies across different clinical settings.[40,42] In the PROMPT-HF (Pragmatic Trial of Messaging to Providers about Treatment of Heart Failure) trial, individualized EHR alerts increased the likelihood of adding a recommended GDMT class in ambulatory patients with HFrEF.[40] However, PROMPT-AHF (Pragmatic Trial of Messaging to Providers about Treatment of Acute Heart Failure) demonstrated that alerts do not uniformly improve comprehensive GDMT initiation in hospitalized patients, highlighting the importance of workflow, timing, clinician engagement, and alert fatigue.[42]

More recently, AI-guided approaches for GDMT optimization are showing a potential evolution from passive risk prediction toward longitudinal treatment support.[43] Agentic AI represents a further extension of this concept. Unlike traditional predictive models that generate a single probability or classification, agentic systems are designed to perform multistep, goal-directed tasks using clinical information, external tools, memory, and iterative reasoning.[44,45]

In HF, a future clinician-supervised agent could potentially review blood pressure, heart rate, renal function, potassium levels, medications, symptoms, and recent clinical events; identify opportunities for initiation or titration of GDMT; determine whether guideline-based eligibility criteria are satisfied; identify required laboratory monitoring; and flag deterioration that warrants clinician review or referral.[43,44] This could allow AI to move beyond

identifying a therapeutic medication initiation, dose titration, escalation of diuretic therapy, or if referral for advanced HF therapies should remain clinician supervised. Human-in-the-loop frameworks, explicit authorization boundaries, transparent documentation of AI actions, and mechanisms for clinician override will be important if agentic systems are integrated into cardiovascular care.[44,46-48]

6. ADVANCED HEART FAILURE STRATIFICATION

This longitudinal approach may be especially relevant to advanced HF. Recognition of patients approaching Stage D HF remains challenging, and referral for advanced HF therapies may occur late.[49]

Models incorporating repeated hospitalizations, medication intolerance, laboratory abnormalities, hemodynamics, imaging, functional status, and healthcare utilization could potentially identify patients whose disease trajectory suggests failure of conventional medical therapy. EHR-based deep-learning models have already demonstrated the feasibility of predicting mortality or referral for advanced HF therapies from routinely collected clinical data.[35,39]

Rather than waiting for a single marker of advanced disease, AI may allow several weak but clinically important signals of deterioration to be considered simultaneously.[35,39,50] If prospectively validated, automated identification could prompt earlier evaluation by advanced HF teams and potentially improve the timing of consideration for mechanical circulatory support or heart transplantation.[39,49] This application may be particularly useful for identifying patients who have not yet been evaluated by an advanced HF team despite accumulating evidence of disease progression.[39]

7. CONTINUOUS MONITORING AND OUTCOMES

The expanding applications of AI in HF suggest a potential shift from episodic, reactive care toward continuous and anticipatory disease management. Traditionally, HF recognition, diagnostic evaluation, treatment, and assessment of disease progression occur at discrete clinical encounters. However, the trajectory toward symptomatic or advanced HF develops longitudinally, with signals of deterioration often distributed across ECGs, echocardiograms, laboratory measurements, medication changes, hospital encounters, symptoms, and other components of the EHR.[27,51] AI offers a framework through which these otherwise fragmented data may be analyzed together, potentially allowing clinicians to recognize disease and intervene earlier in its course.[51,52]

One emerging tool for constant monitoring utilizes AI algorithms based on data collected from smart wearable devices, especially for those with chronic heart failure to prevent further heart failure exacerbation.[51,53] Noninvasive wearable devices such as patches, smartwatches, and sensor-enabled garments can collect signals, which may subsequently be integrated using AI or machine-learning algorithms.[51,53,54] Other noninvasive technologies, including remote dielectric sensing, can provide additional information regarding congestion. However, false-positive alerts, device adherence, data integration, and financial accessibility are some barriers to widespread implementation.[53,54]

Continuous reassessment may be particularly important in HF because risk is dynamic rather than fixed. New laboratory abnormalities, medication intolerance, worsening congestion, recurrent hospitalizations, changes in cardiac function, or patient-reported symptoms may meaningfully alter the patient's clinical trajectory.[51,55]

Risk prediction alone will have limited clinical value unless it produces an actionable change in management. A model that accurately predicts hospitalization without altering treatment may improve prognostic knowledge without necessarily improving outcomes.[55] Therefore the next generation of HF AI should increasingly be evaluated according to whether it facilitates appropriate therapeutic action rather than discrimination metrics alone.

The ultimate end points of these systems should extend beyond model accuracy and include clinically meaningful outcomes such as earlier diagnosis, improved GDMT use, reduction in HF hospitalization, appropriate advanced HF referral, and improved quality of life and mortality.[53,55]

Studies examining AI-enabled remote monitoring and its application in HF are summarized in Table 2.[56-59]

8. PATIENT ENGAGEMENT AND CLINICAL IMPACT

AI may also change how patients interpret and use their health data. Generative AI and conversational systems could translate complex medical terminology, laboratory results, imaging findings, and treatment recommendations into information tailored to an individual's health literacy.[60-62]

These tools may promote patient autonomy by helping individuals understand their diagnosis, recognize concerning symptoms, adhere to medications, and participate more actively in treatment decisions. Emerging agentic systems could ultimately connect patient-reported symptoms and home monitoring with the clinical care team, although such applications require careful safeguards against inaccurate recommendations and inappropriate autonomous decision-making.[44,60]

AI could also be integrated into patient education through tools such as chatbots embedded within patient portals, where patients could ask questions about symptoms, medications, test results, or treatment plans in a comprehensible manner. These tools may provide personalized explanations based on a patient's health

SOURCE	INTERVENTION DETAILS	ASSESSMENT
Olivella et al., 2026	Evaluated a conversational AI system providing weekly automated telephone follow-up to collect symptoms and vital signs and then generate alerts for nurse review.	Included 86 intervention patients and 40 controls. Completed 91.7% of scheduled calls, with improved patient reported HF health status and exploratory signals for better clinical outcomes.
Klein et al., 2025	Developed a ML model using ECG, seismocardiography, and photoplethysmography signals from a wearable sensor to estimate PCWP.	A multicenter prospective study recruited 310 patients with HFrEF. The model estimated PCWP with a mean error of 1.04 ± 5.57 mm Hg compared with invasive measurements.
Herkert et al., 2025	Developed multiparameter predictive models using physiological and activity data collected from wrist worn sensors to detect HF deterioration.	Evaluated 17 patients. The best model demonstrated 97.2% specificity and 5.3% sensitivity, highlighting limitations related to data quality and sample size.
Stehlik et al., 2020	Used a wearable multi-sensor chest patch and ML algorithms to monitor physiological parameters and predict HF hospitalization.	Evaluated 100 patients. Predicted HF rehospitalization with 76-88% sensitivity and 85% specificity. The median time between initial alert and readmission was 6.5 (4.2-13.7) days.

Table 2 Evidence supporting the use of artificial intelligence and digital technologies for continuous monitoring, remote assessment, and prediction of heart failure-related outcomes. HF: heart failure; EHR: electronic health record; AI: artificial intelligence; ML: machine learning; PCWP: pulmonary capillary wedge pressure

SOURCE	INTERVENTION DETAILS	ASSESSMENT
King et al., 2025	Used GPT-4 to simplify 143 HF related patient education materials collected from websites of 10 leading cardiology institutions.	The median reading grade decreased from 10.3 to 7.3 ($P < .001$). No revised materials were rated less accurate or comprehensive, and 23.1% were rated more comprehensive.
Kozaily et al., 2024	30 HF diagnosis, management, and prognosis questions submitted to ChatGPT-3.5 and Bard.	2 HF specialists assessed accuracy and consistency; ChatGPT was mostly appropriate in 90% of questions and 93% consistent, but hallucinations and outdated recommendations occurred.
King et al., 2024	Evalu8ated GPT-3.5 and GPT-4 responses to 107 HF related questions covering basic knowledge management, and prognosis.	Cardiologists assessed accuracy and reproducibility. GPT-4 provided correct information for all 107 questions, with 83.2% responses rated comprehensive and 100% reproducible.

Table 3 Studies evaluating the use of artificial intelligence in patient engagement and the potential impact on heart failure care. HF: heart failure

literacy and individual care plan, allowing patients to participate more actively in decisions about their health.[60,61,63,64]

This may be particularly relevant in HF, where medication regimens are complex, self-monitoring is important, and patients must frequently interpret changes in weight, edema, blood pressure, and symptoms. Studies of large language models suggest that these systems can improve the readability of patient educational information, although accuracy and actionability remain variable and require human oversight.[61,63,65]

Future patient-facing agents could potentially go beyond answering isolated questions. With appropriate safeguards, they might help patients organize home blood pressure and weight measurements, reinforce medication schedules, identify missing follow-up laboratory tests, summarize clinician instructions, or prompt patients to contact their healthcare team when predefined concerning changes occur. Importantly, such systems should complement rather than replace established HF disease-management programs and clinician-patient communication.[44,60]

Table 3 summarizes the studies evaluating AI-generated patient education materials and their clinical utility in HF.[61,64,66]

9. CLINICAL IMPLEMENTATION, LIMITATIONS, AND FUTURE DIRECTIONS

The benefits of AI in HF may depend on how equitably these technologies are implemented. Figure 2 provides an overview of AI applications across the HF care continuum. Patients with limited internet access, limited English proficiency, lower digital or health literacy, disabilities, or fewer healthcare resources may be less likely to benefit from AI-based tools. Algorithms trained primarily within large academic healthcare systems may also perform differently when deployed across populations with different demographics, comorbidities, disease prevalence, or patterns of healthcare access.[67,68]

External validation across diverse health systems is essential before broad deployment. AI tools should aim to reduce existing gaps in HF care rather than widen the gap between patients who have access to advanced tools and those who do not.[67]

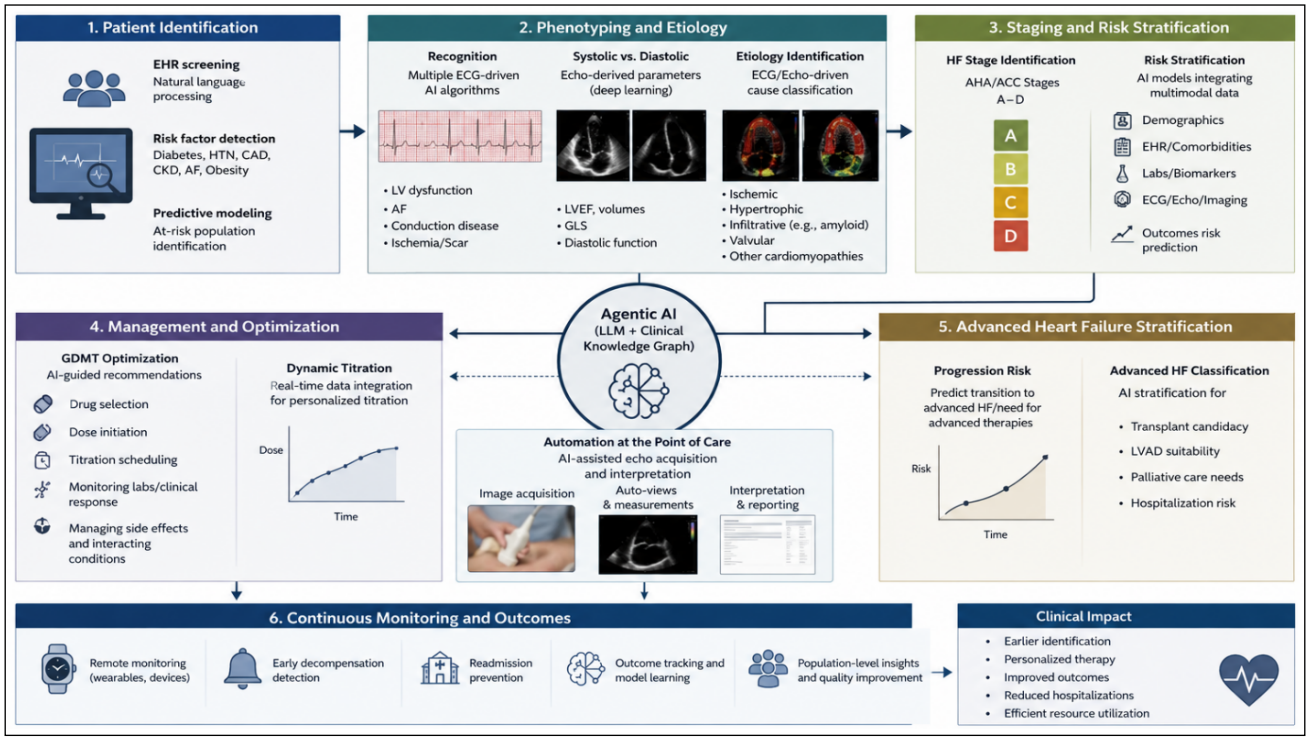


Figure 2 Artificial intelligence (AI) across the heart failure care continuum, from early identification and phenotyping to risk stratification, treatment optimization, advanced heart failure assessment, continuous monitoring, and patient engagement. Figure created with the assistance of ChatGPT and verified. EHR: electronic health record: HTN: hypertension; CAD: coronary artery disease; CKD: chronic kidney disease; AF: atrial fibrillation; ECG: electrocardiography; LVEF: left ventricular ejection fraction; AHA: American Heart Association; ACC: American College of Cardiology; LVAD: left ventricular assist device; GDMT: guideline directly medical therapy

Several additional challenges must be addressed before AI becomes routinely embedded across the HF continuum.[69] Many published models are evaluated retrospectively, and high discrimination does not establish clinical utility. Prospective implementation studies and randomized trials should assess whether AI-guided strategies improve clinically meaningful end points such as time to diagnosis, GDMT utilization, HF hospitalization, referral for advanced therapies, quality of life, and mortality.[67,70,71]

Model interpretability and calibration remain important, particularly when algorithms are used to influence high-stakes therapeutic decisions. Interoperability between AI platforms and existing EHR systems will also be necessary to permit longitudinal assessment without creating additional clinician workload. Finally, data privacy, cybersecurity, algorithmic bias, hallucination, accountability, and regulatory oversight become increasingly important as systems progress from passive prediction toward autonomous or semiautonomous action.[44,46,69,70]

For AI to have meaningful clinical impact, future studies will need to move beyond retrospective algorithm development toward prospective evaluation within real-world HF workflows.[67,70]

CONCLUSION

The future of AI in HF may be best conceptualized not as a single algorithm but as an integrated, clinician-supervised ecosystem. A patient could initially be identified through EHR- or ECG-based screening, undergo AI-assisted echocardiographic assessment, receive multimodal phenotyping to clarify HF etiology and stage, undergo continuously updated risk assessment, and have treatment gaps identified through clinical decision support.

Patients showing evidence of rapid progression could be prioritized for specialist or advanced HF evaluation, while patient-facing AI could reinforce education, self-management, and follow-up between clinical encounters. In this model, AI would connect recognition, diagnosis, risk stratification, and treatment rather than addressing each component in isolation.

Ultimately, the clinical value of AI will not be determined by whether an algorithm outperforms a clinician on an isolated prediction task but by whether its integration improves the timeliness, consistency, accessibility, and outcomes of HF care. AI should augment clinical judgment by making increasingly complex longitudinal data more actionable while preserving clinician accountability and shared decision-making.

KEY POINTS

- The role of artificial intelligence (AI) in heart failure (HF) is growing very rapidly, but its use in routine clinical practice is evolving slowly. Current evidence shows that there are several areas where AI may improve HF care and also points out the important limitations that need to be addressed.
- AI is increasingly being used across the HF care continuum, including early detection, diagnosis, phenotyping, risk stratification, treatment optimization, and patient monitoring.
- AI-enabled tools using electrocardiograms, echocardiograms, electronic health records, and other clinical data can help to identify HF earlier and recognize high risk patients.
- Continuous monitoring through wearable devices, digital health platforms, and AI-based predictive models have the potential to detect clinical deterioration early and support timely interventions to decrease HF associated hospitalizations and adverse outcomes.
- AI may also increase patient engagement by personalized education, communication, and decision support, but its successful use in clinical practice needs proper validation, integration in existing workflows, transparency, equity and clinician oversight.
- Emerging agentic and multimodal AI systems may move HF care towards a more automated, personalized, and proactive approach, but the evidence showing meaningful improvement in clinical outcomes is still limited.

COMPETING INTERESTS

The authors have no competing interests to declare.

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