BALNEO RESEARCH Balneo and PRM Research Journal
English Edition
e ISSN 2734 - 8458 p ISSN 2734 - 844X ROMANIAN ASSOCIATION OF BALNEOLOGY

Review

The Role of Artificial Intelligence in Cardiac Rehabilitation of Patients with Heart Failure

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Citation: Caloian B., Caloian C.S., Irimie D.A., Mihaila D., Comsa D.H., Fringu F.I., Tomoaia R., Gusetu N.G., Cismaru G.L., Rosu R.O., Pop D. - The Role of Artificial Intelligence in Cardiac Rehabilitation of Patients with Heart Failure
Balneo and PRM Research Journal **2026**, *17(1): 949*

Academic Editor(s):
Constantin Munteanu

Reviewer Officer:
Viorela Bembea

Production Officer:
Camil Filimon

Received: 16.12.2025
Published: 31.03.2026

Reviewers:
Alin Daniel Malaelea
Sebastian Giuvara

Abstract: Heart failure remains a leading cause of morbidity and mortality worldwide. Although cardiac rehabilitation is strongly recommended, its implementation is limited by restricted access, heterogeneous patient profiles, and poor long-term adherence. Artificial intelligence (AI) has emerged as a potential tool to enhance personalization and scalability of rehabilitation programs. A narrative review was conducted using PubMed, Scopus, and Web of Science to identify studies addressing AI applications in heart failure and cardiac rehabilitation. Clinical trials, observational studies, guidelines, and methodological papers were selected based on relevance and scientific rigor. AI techniques—including machine learning, deep learning, reinforcement learning, and natural language processing—are being applied across all phases of cardiac rehabilitation. Applications include risk stratification, individualized exercise prescription, real-time monitoring through wearable devices, anomaly detection, behavioral support, and long-term outcome prediction. Early evidence suggests improved personalization, safety, and patient engagement; however, large-scale outcome data remain limited. Despite promising results, challenges related to data quality, algorithm transparency, bias, clinical integration, and regulatory oversight persist. AI has the potential to transform cardiac rehabilitation in heart failure by enabling adaptive, data-driven, and patient-centered care, provided rigorous validation and ethical implementation are ensured.

Keywords: heart failure, cardiovascular rehabilitation, artificial intelligence, tele-rehabilitation, wearable devices, personalized medicine

1. Introduction

Heart failure (HF) is a major global health problem, affecting more than 64 million people worldwide and representing a leading cause of morbidity, mortality, and healthcare expenditure [1,2]. Despite substantial advances in pharmacological therapies and device-based interventions, many patients with HF continue to experience reduced exercise capacity, poor quality of life, and recurrent hospitalizations [1,3]. These challenges highlight the need for comprehensive management strategies that extend beyond conventional medical treatment.

Cardiac rehabilitation (CR) is a cornerstone of multidisciplinary care for patients with HF. Exercise-based CR programs, incorporating supervised physical training, education, risk factor modification, and psychosocial support, have demonstrated significant improvements in functional capacity, symptoms, and health-related quality of life, with favorable effects on hospitalization risk in selected populations [3–5].

Consequently, international guidelines from major cardiovascular societies recommend CR as an integral component of care for patients with stable HF, particularly those with reduced ejection fraction [6,7].

Despite strong evidence from multiple clinical studies and guideline recommendations, CR remains underutilized in patients with HF. Participation rates are low, and referral to CR programs is inconsistent across healthcare systems [8]. Multiple barriers contribute to this gap, including limited availability of specialized programs, geographic and transportation constraints, patient frailty and comorbidities, lack of individualized exercise prescriptions, and suboptimal long-term adherence [8,9]. Furthermore, the heterogeneity of the HF population—encompassing different phenotypes, functional capacities, and risk profiles—poses additional challenges for standardized, center-based CR models.

Artificial intelligence (AI) and digital health technologies are reshaping cardiovascular medicine. AI, encompassing machine learning, deep learning, and other data-driven analytical techniques, enables the processing and interpretation of large, complex, and multimodal datasets beyond the capacity of traditional statistical approaches [10,11]. In HF care, AI-based models have been increasingly applied to risk stratification, outcome prediction, phenotyping, and clinical decision support, demonstrating promising performance in both research and real-world settings [11,12].

For physicians prescribing cardiac rehabilitation programms, AI offers novel opportunities to overcome existing limitations. By integrating data from electronic health records, wearable sensors, mobile health applications, and patient-reported outcomes, AI-driven systems may enable personalized exercise prescription, dynamic adjustment of training intensity, and real-time safety monitoring [13–15]. Moreover, AI-supported tele-rehabilitation and home-based CR programs have the potential to expand access, improve adherence, and facilitate early detection of clinical deterioration, particularly for patients unable or unwilling to participate in traditional center-based programs [16,17].

Despite growing interest and rapid technological development, the role of AI in cardiac rehabilitation for patients with HF remains limited, and the clinical evidence base is still evolving. Existing studies are heterogenous in methodology, target populations, AI techniques, and outcome measures, making it difficult to draw unified conclusions. A comprehensive synthesis of current applications, supporting evidence, benefits, and limitations is therefore needed to inform clinical practice and guide future research [10,18].

The aim of this review is to critically examine the role of artificial intelligence in cardiac rehabilitation for patients with heart failure. We summarize relevant AI methodologies and data sources, review current clinical evidence, discuss potential benefits and challenges, and highlight future directions for the integration of AI into HF rehabilitation programs.

2. Methods

This manuscript was conducted as a narrative review of the literature focusing on the role of artificial intelligence (AI) in cardiac rehabilitation (CR) for patients with heart failure (HF).

2.1. Search Strategy

A literature search was performed using the electronic databases PubMed/MEDLINE, Scopus, and Web of Science. The search included articles published from January 2010 to December 2025. Combinations of the following keywords and Medical Subject Headings (MeSH) terms were used: "heart failure", "cardiac rehabilitation", "artificial intelligence", "machine learning", "deep learning", "reinforcement learning", "digital health", "tele-rehabilitation", "wearable devices", "remote monitoring". Boolean operators (AND/OR) were applied to combine terms appropriately.

2.2. Eligibility Criteria and Study Selection

Original research articles, randomized controlled trials, observational studies, systematic reviews, meta-analyses, position statements, and clinical guidelines published in English were considered eligible. Articles were included if they addressed:

- Applications of artificial intelligence or advanced analytics in heart failure management;
- AI-supported cardiac rehabilitation or tele-rehabilitation models;
- Digital monitoring, predictive analytics, or decision-support systems relevant to rehabilitation.

Studies not related to heart failure or cardiac rehabilitation, non-peer-reviewed articles, editorials without substantial methodological content, and conference abstracts without full-text availability were excluded.

Articles were screened based on title and abstract for relevance. Full texts of potentially eligible studies were reviewed to assess their contribution to the thematic areas addressed in this review. Reference lists of selected articles were also screened to identify additional relevant publications.

2.3. Data Synthesis

Given the heterogeneity of study designs, AI methodologies, and clinical endpoints, a qualitative synthesis approach was adopted. The search yielded approximately 350 records. After screening for relevance and removal of duplicates, approximately 120 full-text articles were reviewed, of which more than 80 were considered directly relevant and were included in the qualitative synthesis. The selected studies were categorized according to their relevance to the different phases of cardiac rehabilitation (assessment, exercise prescription, monitoring, adherence, and long-term follow-up), as well as to benefits, limitations, and future perspectives.

3. Results

3.1. Definition and Phases of Cardiac Rehabilitation

Cardiac rehabilitation (CR) is a comprehensive, multidisciplinary intervention designed to improve the physical, psychological, and social functioning of patients with cardiovascular disease, including those with heart failure (HF). It integrates structured exercise training, patient education, lifestyle modification, psychosocial support, and optimization of medical therapy with the goal of reducing morbidity, preventing disease progression, and improving quality of life [19,20]. In patients with HF, CR programs must account for disease severity, comorbidities, functional limitations, and the dynamic clinical course of the disease.

Traditionally, CR is organized into three sequential phases, although modern programs increasingly adopt flexible and hybrid models, particularly for patients with chronic HF [19–21].

Phase I (inpatient cardiac rehabilitation) begins during hospitalization for acute decompensated HF or following a major cardiovascular event. The primary objectives of this phase are early mobilization, prevention of physical deconditioning, patient education, and risk stratification. Interventions typically include low-intensity mobilization, breathing exercises, education on HF self-care, medication adherence, and recognition of warning symptoms. Phase I also serves as a critical period for motivating patients and facilitating referral to outpatient CR programs [20,21].

Phase II (early outpatient cardiac rehabilitation) represents the core structured component of CR and is usually initiated within weeks after hospital discharge once the patient is clinically stable. This phase is conducted in outpatient or community-based settings and involves supervised exercise training tailored to the patient's functional capacity and clinical status, alongside education and behavioral interventions. In patients with HF, exercise modalities may include aerobic training, resistance training, and, in selected cases, inspiratory muscle training. Phase II CR has been shown to improve peak oxygen uptake, exercise tolerance, symptoms, and health-related quality of life, and it is strongly endorsed by international guidelines for eligible patients with HF [21–23].

Phase III (long-term maintenance cardiac rehabilitation) focuses on sustaining and increasing the benefits achieved during supervised rehabilitation through long-term lifestyle modification and continued physical activity. This phase is often less structured and may involve home-based or community-based exercise programs, with periodic clinical follow-up. For patients with HF, Phase III CR is particularly important due to the chronic and progressive nature of the disease, the high risk of functional decline, and the need for ongoing self-management. However, adherence during this phase is frequently suboptimal, highlighting the need for innovative approaches such as tele-rehabilitation and digital health solutions to support long-term engagement [22–24].

Across all phases, effective CR in HF requires individualized assessment, continuous monitoring, and close coordination among healthcare professionals. The increasing availability of digital technologies and artificial intelligence offers new opportunities to enhance continuity of care across CR phases, particularly by facilitating transitions from supervised to home-based rehabilitation models.

3.2. Core Components of Cardiac Rehabilitation in Heart Failure

Cardiac rehabilitation (CR) for patients with heart failure (HF) is a complex intervention comprising several core components that together aim to improve physical capacity, clinical stability, and long-term self-management. International position statements and guidelines emphasize that CR should be delivered by a multidisciplinary team and tailored to the individual patient's clinical profile, functional status, and psychosocial needs [25,26].

Exercise training represents the central component of CR in HF. Aerobic exercise, typically performed at moderate intensity, has consistently been shown to improve peak oxygen uptake, submaximal exercise capacity, endothelial function, and symptoms in patients with stable HF. Resistance training is increasingly recommended as an adjunct to aerobic exercise to counteract skeletal muscle weakness, sarcopenia, and frailty, which are common in HF populations. In selected patients, additional modalities such as inspiratory muscle training or interval training may be incorporated to further enhance functional outcomes [26–28].

Patient education and self-management support are essential elements of CR. Educational interventions focus on improving patients' understanding of HF pathophysiology, medication adherence, symptom recognition, dietary recommendations (e.g., sodium and fluid management), and the importance of physical activity. Enhanced self-care behaviors have been associated with reduced hospitalization rates and improved quality of life in HF patients, underscoring the value of structured education within CR programs [29].

Risk factor modification is another key pillar of CR. Although HF is often the end stage of various cardiovascular diseases, optimization of modifiable risk factors—including blood pressure control, glycemic management, lipid profile optimization, smoking cessation, and weight management—remains clinically relevant. CR programs provide an integrated framework for addressing these factors in conjunction with exercise and lifestyle counseling [25,30].

Psychosocial support is particularly important in HF, given the high prevalence of depression, anxiety, and social isolation in this population. Psychological distress has been associated with poorer adherence to treatment, reduced participation in CR, and worse clinical outcomes. CR programs commonly include psychological assessment, counseling, and stress management strategies to address these issues and improve overall well-being [26,31].

Finally, **optimization of medical therapy and multidisciplinary coordination** are integral to effective CR. Close collaboration among cardiologists, rehabilitation physicians, nurses, physiotherapists, dietitians, and psychologists ensures that exercise prescriptions and lifestyle interventions are aligned with guideline-directed medical therapy and adjusted as the patient's clinical condition evolves [25,26].

3.3. Current Challenges in Heart Failure Rehabilitation

Despite strong evidence supporting the benefits of cardiac rehabilitation in HF, multiple challenges limit its implementation, uptake, and long-term effectiveness. These barriers operate at the patient, provider, and healthcare system levels and contribute to the persistent underutilization of CR in routine HF care [32].

One of the most significant challenges is the **low referral and participation rate** among eligible HF patients. Compared with patients with ischemic heart disease, individuals with HF are less frequently referred to CR programs and less likely to enroll when referred. Advanced age, frailty, multiple comorbidities, and socioeconomic factors further reduce participation, particularly among women and older adults [32,33].

Clinical heterogeneity represents another major obstacle. HF encompasses a broad spectrum of phenotypes, including heart failure with reduced, mildly reduced, and preserved ejection fraction, as well as varying degrees of functional limitation and comorbidity burden. Standardized CR protocols may not adequately address this diversity, leading to concerns regarding safety, effectiveness, and personalization of exercise prescriptions [26,33].

Logistical and organizational barriers also limit access to CR. Center-based programs require frequent in-person visits, which may be challenging for patients with limited mobility, transportation difficulties, or geographic constraints. These issues are particularly relevant for HF patients, who often experience fluctuating symptoms and recurrent hospitalizations that disrupt continuity of care [32].

Adherence and long-term maintenance pose additional challenges, especially during the transition from supervised (Phase II) to unsupervised (Phase III) rehabilitation. Sustaining lifestyle changes and regular physical activity over time remains difficult for many patients with HF, contributing to the attenuation of benefits achieved during structured CR programs [31,33].

Finally, **resource constraints and workforce limitations** affect the scalability of HF-specific CR programs. Limited availability of trained personnel, insufficient reimbursement models, and variability in program quality across regions hinder widespread implementation. These challenges underscore the need for innovative, scalable solutions—such as tele-rehabilitation and AI-supported CR models—to enhance access, personalization, and long-term engagement [32]

3.4. Artificial Intelligence in Healthcare: Concepts and Methods

Artificial intelligence (AI) refers to a broad class of computational techniques that enable machines to perform tasks traditionally requiring human intelligence, such as learning from data, pattern recognition, prediction, and decision-making. In healthcare, AI has gained increasing attention due to its ability to analyze large-scale, complex, and heterogeneous datasets and to support clinical decision-making across prevention, diagnosis, treatment, and rehabilitation [34,35]. In cardiovascular medicine, AI applications have expanded rapidly, driven by the availability of digital health data and advances in computing power.

Definitions and Subfields of Artificial Intelligence

AI in healthcare primarily encompasses several interrelated subfields. **Machine learning (ML)** refers to algorithms that learn patterns from data and improve their performance without explicit programming. ML approaches are commonly categorized into supervised learning, unsupervised learning, and semi-supervised learning, depending on the availability of labeled outcomes. These methods are widely used for risk prediction, classification, and outcome forecasting in cardiovascular disease [35,36].

Deep learning (DL) is a subset of ML that uses artificial neural networks with multiple hidden layers to model complex, non-linear relationships. DL techniques have demonstrated particular strength in processing high-dimensional data such as medical imaging, waveform signals, and continuous data streams from wearable devices. In cardiology, DL models have been applied to echocardiography interpretation, electrocardiogram analysis, and automated phenotyping of heart failure populations [36,37].

Natural language processing (NLP) enables the extraction and interpretation of unstructured textual data, such as clinical notes, discharge summaries, and patient-reported narratives. NLP methods facilitate the integration of real-world clinical information into AI models and have been used to identify comorbidities, symptoms, and outcomes relevant to heart failure management and rehabilitation [38].

Reinforcement learning represents another emerging AI paradigm, in which algorithms learn optimal decision-making strategies through trial-and-error interactions with an environment. Although still limited in clinical application, reinforcement learning holds promise for dynamic treatment optimization and adaptive exercise prescription, making it conceptually relevant for cardiac rehabilitation programs [39].

Data Sources Relevant to Cardiac Rehabilitation

The effectiveness of AI systems in cardiac rehabilitation depends largely on the availability and quality of relevant data sources. **Electronic health records (EHRs)** provide longitudinal clinical data, including demographics, diagnoses, laboratory values, medications, and outcomes, forming the backbone of many AI-based prediction models in HF [35,38].

Wearable sensors and connected devices generate continuous physiological and behavioral data, such as heart rate, physical activity, energy expenditure, sleep patterns, and in some cases rhythm monitoring. These data streams are particularly valuable in the rehabilitation setting, where monitoring exercise response, adherence, and early signs of clinical deterioration is essential [40].

Patient-reported outcome measures (PROMs) capture symptoms, functional status, and quality of life, which are central targets of CR interventions. Integration of PROMs into AI-driven platforms enables more patient-centered and responsive rehabilitation strategies [41].

Finally, **mobile health (mHealth) applications and tele-rehabilitation platforms** act as both data collection tools and intervention delivery systems. These platforms facilitate bidirectional communication between patients and healthcare providers and enable real-time feedback, making them well suited for AI-supported CR models that adapt to individual patient needs over time [40,41].

Relevance of AI Methods to Cardiac Rehabilitation

The combination of advanced AI methodologies with multimodal data sources creates new opportunities for cardiac rehabilitation in HF. AI models can support patient stratification, personalize exercise prescriptions, monitor safety during training, and enhance long-term adherence through adaptive feedback mechanisms. Importantly, these technologies also enable a shift from episodic, center-based rehabilitation toward continuous, data-driven care across all phases of CR. However, the clinical integration of AI requires careful consideration of data quality, interpretability, and alignment with existing rehabilitation workflows, which will be discussed in subsequent sections

3.5. Applications of Artificial Intelligence in Cardiac Rehabilitation for Patients with Heart Failure

The integration of artificial intelligence (AI) into cardiac rehabilitation (CR) has the potential to transform traditional rehabilitation models by enabling personalized, adaptive, and data-driven interventions. In patients with heart failure (HF), AI applications span patient selection, exercise prescription, remote monitoring, behavioral support, and clinical decision support, addressing many of the limitations of conventional CR programs.

AI-Based Patient Stratification and Risk Prediction

One of the most mature applications of AI in HF care is patient stratification and risk prediction. Machine learning models can integrate demographic characteristics, clinical variables, laboratory values, imaging findings, and longitudinal health records to identify patients most likely to benefit from CR and those at increased risk of adverse events during rehabilitation [42,43]. In the CR context, AI-driven risk stratification may support safer exercise prescription by identifying patients at higher risk of decompensation, arrhythmias, or hospitalization.

Predictive models have also been developed to forecast outcomes such as functional decline, hospital readmission, and mortality in HF populations. These tools may help clinicians tailor the intensity and monitoring level of rehabilitation programs and guide shared decision-making with patients [44].

Personalized and Adaptive Exercise Prescription

Exercise prescription in HF rehabilitation traditionally relies on baseline functional assessments and standardized progression protocols. AI enables a shift toward **precision rehabilitation**, in which exercise type, intensity, duration, and progression are continuously adapted based on individual responses. By analyzing physiological signals such as heart rate dynamics, activity patterns, and perceived exertion, AI algorithms can dynamically adjust training loads to optimize effectiveness while maintaining safety [45].

Reinforcement learning and adaptive ML approaches are particularly promising in this domain, as they can learn optimal exercise strategies through repeated interactions with patient data. Such systems may be especially valuable for heterogeneous HF populations, where responses to exercise vary widely [46].

Remote and Home-Based Cardiac Rehabilitation

AI plays a central role in enabling remote and home-based CR models, which are increasingly recognized as effective alternatives to center-based programs. AI-supported tele-rehabilitation platforms can monitor exercise performance, detect deviations from prescribed activity, and provide real-time feedback to patients and clinicians [47]. These approaches are particularly relevant for HF patients who face logistical barriers to in-person CR participation.

By automating data analysis and alert generation, AI systems may reduce clinician workload while improving surveillance and continuity of care. Early identification of declining activity levels or abnormal physiological responses may prompt timely intervention and prevent clinical deterioration [48].

Wearables and Sensor-Based Monitoring

Wearable technologies generate large volumes of continuous data that are well suited for AI-based analysis. In HF rehabilitation, wearables can capture heart rate, physical activity, sleep patterns, and, in some devices, rhythm disturbances. AI algorithms can process these data to identify patterns indicative of overexertion, poor adherence, or early HF worsening [49].

Anomaly detection techniques are particularly relevant in this context, enabling the identification of subtle changes from an individual's baseline rather than relying on population-level thresholds. This individualized monitoring approach aligns closely with the goals of personalized CR in HF [50].

Behavioral Support, Engagement, and Adherence

Sustained engagement and adherence remain major challenges in CR, particularly during long-term maintenance phases. AI-driven behavioral support tools, including virtual coaches and conversational agents, have been developed to provide personalized feedback, motivation, and education. These systems can adapt messaging based on patient behavior, preferences, and progress, thereby enhancing self-efficacy and long-term adherence [51].

In HF populations, such tools may support symptom monitoring, medication adherence, and lifestyle modification, complementing exercise-based interventions and reinforcing self-management behaviors essential for long-term outcomes.

AI-Based Clinical Decision Support Systems

AI-driven clinical decision support systems (CDSS) can assist healthcare professionals supervising CR programs by synthesizing multimodal data into actionable insights. In HF rehabilitation, CDSS may support decisions related to exercise progression, safety alerts, referral to higher levels of care, or modification of rehabilitation goals [52].

When integrated into clinical workflows, these systems have the potential to enhance consistency, reduce variability in care delivery, and support multidisciplinary teams. However, successful implementation depends on transparency, interpretability, and alignment with clinical guidelines, which remain critical considerations. Figure 1 presents a conceptual mapping of AI methods across CR phases.

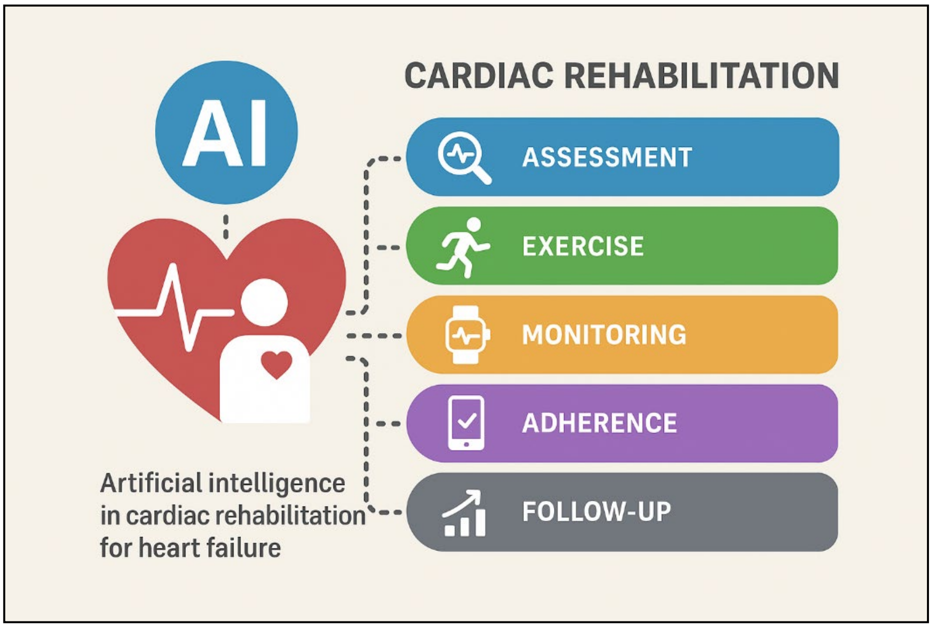

Figure 1. Graphical Abstract. Integration of artificial intelligence (AI) into cardiac rehabilitation for patients with heart failure. AI methods—including machine learning, deep learning, reinforcement learning, and natural language processing—support patient assessment, personalized exercise prescription, continuous monitoring, behavioral engagement, and long-term follow-up, enabling adaptive, data-driven, and patient-centered rehabilitation pathways.

3.6. Evidence from Clinical Studies

The clinical application of artificial intelligence (AI) in cardiac rehabilitation (CR) for heart failure (HF) is an emerging field, with studies ranging from observational analyses and pilot feasibility studies to randomized controlled trials (RCTs). Evidence to date suggests that AI-enabled approaches may enhance patient monitoring, adherence, and outcomes, although high-quality, large-scale trials remain limited.

Observational Studies

Several observational studies have explored the feasibility and safety of AI-supported rehabilitation and monitoring strategies in HF. Tison et al. demonstrated that data from wearable devices, analyzed using AI algorithms, can reliably monitor physiological parameters such as heart rate and physical activity in ambulatory patients, supporting remote supervision during rehabilitation programs [45]. Similarly, Clifton et al. applied machine learning techniques to continuous sensor data from patients with HF, enabling early detection of physiological deterioration and highlighting the potential of AI-driven monitoring for timely clinical intervention [50]. These studies indicate that AI-based surveillance during rehabilitation is feasible and may improve safety in real-world HF populations.

Randomized Controlled Trials

Randomized trials have begun to evaluate the effectiveness of AI-assisted or tele-rehabilitation interventions compared with standard care. The TIM-HF2 trial assessed a structured telemedical management strategy incorporating automated data transmission and algorithm-based alerts in patients with chronic HF. This intervention resulted in a significant reduction in days lost due to unplanned cardiovascular hospitalizations and all-cause mortality, underscoring the potential clinical benefits of AI-supported remote care models [48].

Frederix et al. evaluated a home-based cardiac telerehabilitation program incorporating digital monitoring and automated feedback mechanisms. Participants achieved improvements in exercise capacity and health-related quality of life comparable to those observed in conventional center-based CR programs, with high adherence rates [47]. Additional randomized and pilot studies of home-based and digitally supported CR interventions have reported favorable effects on physical activity levels, functional capacity, and patient engagement, although heterogeneity in study design and outcome measures remains a limitation [17].

Ongoing Trials and Registries

Beyond completed trials, several ongoing studies and registries are investigating the role of AI in HF rehabilitation, including AI-guided exercise prescription, adherence monitoring, and risk stratification. These initiatives aim to provide robust data on safety, effectiveness, cost-efficiency, and scalability in diverse HF populations, and to support the development of precision rehabilitation strategies [53].

Summary of Current Evidence

Overall, current clinical evidence supports the feasibility and potential effectiveness of AI-assisted CR in patients with HF. Observational studies demonstrate reliable remote monitoring and early detection of clinical deterioration, while randomized trials suggest improvements in clinical outcomes, functional capacity, and adherence. Nevertheless, the evidence base remains heterogeneous and relatively limited, emphasizing the need for large, multicenter RCTs with standardized endpoints and long-term follow-up to establish best practices and inform clinical guidelines.

4. Discussion

4.1. Benefits of AI-Enhanced Cardiac Rehabilitation in Heart Failure

The integration of artificial intelligence (AI) into cardiac rehabilitation (CR) programs offers several potential advantages over traditional rehabilitation models, particularly for patients with heart failure (HF). By enabling data-driven, adaptive, and scalable interventions, AI-enhanced CR has the potential to improve clinical outcomes, patient experience, and healthcare system efficiency.

Improved Personalization of Rehabilitation Programs

One of the most significant benefits of AI-enhanced CR is the ability to deliver highly personalized rehabilitation interventions. Traditional CR programs often rely on standardized exercise prescriptions and periodic reassessments, which may not adequately capture individual variability in functional capacity, symptom burden, and response to training. AI algorithms can continuously analyze multimodal data—including physiological signals, activity patterns, and patient-reported outcomes—to dynamically tailor exercise intensity, progression, and recovery periods to individual needs [54].

This individualized approach is particularly relevant in HF populations, characterized by marked heterogeneity in disease phenotype, comorbidities, and functional limitations. Personalized rehabilitation strategies may enhance both safety and effectiveness, reducing the risk of overexertion while maximizing functional gains.

Enhanced Access of Cardiac Rehabilitation

Limited access to CR remains a major challenge worldwide, especially for patients with HF who face mobility limitations, geographic barriers, or competing health demands. AI-enabled digital and tele-rehabilitation platforms can support the delivery of CR outside traditional clinical settings, thereby expanding access to underserved populations [55].

Improved Adherence and Patient Engagement

Adherence to CR and long-term lifestyle modification remains suboptimal, particularly beyond the supervised phases of rehabilitation. AI-driven behavioral support tools, such as adaptive feedback systems and virtual coaching, can promote sustained engagement by providing personalized motivation, goal setting, and reinforcement based on individual behavior and preferences [56].

In HF patients, enhanced engagement may translate into improved self-care behaviors, greater physical activity levels, and better symptom management. Continuous monitoring and timely feedback can also increase patients' sense of accountability and empowerment, which are key determinants of adherence.

Early Detection of Clinical Deterioration and Improved Safety

AI-based monitoring systems can detect subtle physiological and behavioral changes that may precede clinical deterioration in HF patients. By analyzing trends in activity levels, heart rate patterns, and other sensor-derived data, AI algorithms can identify deviations from individual baselines and generate early warnings for patients and clinicians [57].

This capability is particularly valuable during exercise-based rehabilitation, where timely detection of adverse responses can improve safety and prevent hospitalizations. Early intervention triggered by AI-based alerts may also support proactive care and reduce the burden of acute decompensation.

Potential Cost-Effectiveness and Healthcare System Benefits

Although comprehensive economic evaluations remain limited, AI-enhanced CR has the potential to be cost-effective by reducing hospital readmissions, optimizing resource utilization, and enabling more efficient delivery of rehabilitation services. Remote monitoring and automated decision support may decrease the need for frequent in-person visits while maintaining or improving clinical outcomes [58,59].

From a healthcare system perspective, AI-supported CR aligns with broader efforts to shift care toward value-based, preventive, and patient-centered models. By improving outcomes and expanding access, these technologies may contribute to more sustainable HF management strategies.

Support for Multidisciplinary and Data-Driven Care

AI tools can facilitate integration and coordination across multidisciplinary CR teams by synthesizing complex data into actionable insights. This may improve consistency in care delivery, support clinical decision-making, and enhance communication among healthcare professionals involved in HF rehabilitation [60].

Moreover, the systematic collection and analysis of rehabilitation data can generate real-world evidence to inform continuous program improvement and future research, reinforcing a learning healthcare system approach.

4.2. Limitations, Challenges, and Ethical Considerations

Despite the promising potential of artificial intelligence (AI)–enhanced cardiac rehabilitation (CR) for patients with heart failure (HF), several limitations and challenges must be addressed before widespread clinical implementation can be achieved. These issues span technical, clinical, organizational, ethical, and regulatory domains and are critical for ensuring safe, effective, and equitable use of AI in rehabilitation.

Technical and Methodological Challenges

A major limitation of AI applications in CR relates to **data quality and availability**. AI models rely on large volumes of high-quality, representative data, yet rehabilitation data are often fragmented across electronic health records, wearable devices, and patient-reported outcomes. Incomplete, noisy, or biased datasets may compromise model performance and generalizability, particularly in heterogeneous HF populations [61].

Algorithm bias represents another significant concern. Many AI models are trained on datasets that underrepresent older adults, women, and patients with multiple comorbidities—groups that constitute a substantial proportion of the HF population. As a result, AI-driven recommendations may be less accurate or less safe for these patients, potentially exacerbating health disparities [62].

Additionally, the **lack of transparency and interpretability** of complex AI models, particularly deep learning systems, limits clinical trust and adoption. "Black-box" models that provide predictions without clear explanations may be difficult for clinicians to validate, challenge, or integrate into shared decision-making processes [63].

Clinical and Organizational Barriers

From a clinical perspective, integrating AI tools into CR workflows remains challenging. Many CR programs operate with limited resources, and the introduction of AI systems may require substantial investments in infrastructure, training, and technical support. Clinician acceptance is another barrier, as healthcare professionals may be reluctant to rely on algorithmic recommendations without robust evidence, interpretability, and clear accountability structures [64].

Moreover, the **evidence base for AI-enhanced CR remains heterogeneous**, with variability in study design, AI methods, endpoints, and follow-up duration. The lack of standardized outcome measures and reporting frameworks complicates the comparison of studies and limits the translation of research findings into clinical guidelines [65].

Regulatory and Legal Considerations

AI applications in healthcare raise complex **regulatory and legal questions**, particularly when used to guide clinical decisions in rehabilitation. Regulatory frameworks for AI-based medical devices are still evolving, and requirements for validation, certification, and post-market surveillance vary across jurisdictions. Ensuring compliance with regulatory standards while maintaining innovation remains a significant challenge [66].

Liability issues also remain unresolved. When AI systems contribute to clinical decision-making, determining responsibility for adverse events—whether attributable to clinicians, developers, or healthcare institutions—can be difficult. Clear governance structures and accountability mechanisms are therefore essential [67].

Ethical Considerations and Patient-Centered Care

Ethical considerations are central to the deployment of AI in CR. **Data privacy and security** are particularly critical, as AI-driven rehabilitation systems often rely on continuous data collection from wearable devices and mobile platforms. Ensuring robust data protection, informed consent, and transparency in data use is essential to maintain patient trust [62,68].

Finally, there is a risk that increased reliance on AI-driven automation could undermine the **human-centered nature of rehabilitation**, which relies heavily on therapeutic relationships, motivation, and individualized support. AI should therefore be viewed as a tool to augment—not replace—clinical expertise and patient–provider interaction. Maintaining patient autonomy, shared decision-making, and equity must remain central goals in AI-enhanced CR models [63,68]

4.3. Future Perspectives

The integration of artificial intelligence (AI) into cardiac rehabilitation (CR) for patients with heart failure (HF) is still in its early stages, and several developments are expected to shape the future of this rapidly evolving field. Advances in data science, digital health infrastructure, and clinical research methodologies are likely to further enhance the role of AI in delivering effective, personalized, and scalable rehabilitation programs.

Toward Precision Cardiac Rehabilitation

Future AI-enabled CR programs are expected to move beyond generalized protocols toward **precision rehabilitation**, in which interventions are tailored to individual patient characteristics, risk profiles, and real-time physiological responses. By integrating multimodal data—including genomics, imaging, wearable sensor data, and patient-reported outcomes—AI systems may enable more refined phenotyping of HF patients and more accurate prediction of training response and risk [69].

Such approaches could facilitate adaptive exercise prescriptions that evolve dynamically over time, supporting optimal training intensity and recovery while minimizing adverse events. Precision CR may be particularly beneficial for complex HF populations, including older adults and patients with multiple comorbidities.

Integration of Advanced Wearables and Digital Biomarkers

The continued development of wearable technologies and digital biomarkers will likely expand the scope and accuracy of AI-driven rehabilitation. Next-generation sensors capable of measuring physiological, biomechanical, and behavioral parameters may provide richer datasets for AI algorithms, enabling more sensitive detection of changes in functional status and early signs of clinical deterioration [70].

Digital biomarkers derived from continuous monitoring may also serve as novel endpoints in clinical trials, supporting more efficient evaluation of rehabilitation interventions and accelerating evidence generation.

Hybrid and Adaptive Rehabilitation Models

Hybrid CR models that combine center-based and home-based components are expected to play a growing role in HF management. AI systems may support the seamless transition between supervised and unsupervised phases of rehabilitation by adjusting monitoring intensity and feedback based on patient risk and performance [71].

Adaptive rehabilitation pathways could improve long-term adherence and sustainability by providing ongoing support beyond the traditional duration of CR programs. These models align with the increasing emphasis on lifelong secondary prevention and chronic disease management.

Strengthening Clinical Evidence and Standardization

To support broader adoption, future research must prioritize **large, multicenter randomized controlled trials** with standardized outcome measures and long-term follow-up. The use of common data models, transparent reporting of AI methodologies, and adherence to emerging standards for AI evaluation in healthcare will be critical for comparability and reproducibility [72,73].

Collaboration among clinicians, data scientists, engineers, and regulatory bodies will be essential to ensure that AI tools are clinically relevant, robust, and aligned with patient needs.

Regulatory, Ethical, and Policy Developments

As AI becomes increasingly integrated into CR, regulatory and policy frameworks are expected to mature. Clear guidance on validation, certification, data governance, and accountability will be necessary to ensure safe and ethical deployment. International initiatives aimed at developing trustworthy and human-centered AI may help harmonize standards and support responsible innovation [74].

In parallel, reimbursement models and health policy decisions will play a crucial role in determining the sustainability and scalability of AI-enhanced CR programs. Demonstrating clinical effectiveness, cost-efficiency, and equity will be key to securing long-term support from healthcare systems [75].

5. Conclusions

Artificial intelligence is emerging as a transformative tool in cardiac rehabilitation for patients with heart failure, offering new opportunities to address long-standing limitations in accessibility, personalization, and long-term adherence. By enabling continuous data integration, adaptive exercise prescription, and real-time monitoring, AI-enhanced rehabilitation models have the potential to complement traditional center-based programs and support more patient-centered, scalable approaches to care.

Current evidence suggests that AI-supported cardiac rehabilitation is feasible and may improve functional capacity, patient engagement, and early detection of clinical deterioration. Tele-rehabilitation platforms, wearable technologies, and machine learning–based decision support systems have demonstrated promising results, particularly in extending rehabilitation services beyond conventional settings. However, the overall evidence base remains heterogeneous, and robust multicenter trials with standardized outcomes and long-term follow-up are still needed to establish definitive clinical benefits and cost-effectiveness.

Several challenges must be addressed before widespread implementation can be achieved. These include issues related to data quality, algorithm transparency, clinical integration, regulatory oversight, and ethical considerations such as bias, privacy, and patient autonomy. Importantly, AI should be viewed as an adjunct to—not a replacement for—clinical expertise and the therapeutic relationship that is central to effective cardiac rehabilitation.

Looking ahead, continued advances in digital health technologies, combined with rigorous clinical evaluation and interdisciplinary collaboration, are likely to accelerate the development of precision cardiac rehabilitation. The successful integration of AI into rehabilitation programs will depend on aligning technological innovation with patient needs, clinical workflows, and health system priorities. If implemented responsibly, AI-enhanced cardiac rehabilitation has the potential to play a meaningful role in improving outcomes and quality of life for patients with heart failure.

Author Contributions: Conceptualization, B.C., D.P. and R.O.R.; resources, C.S.C., D.M.; writing—original draft preparation, B.C., D.A.I., and F.I.F.; writing—G.L.C. and G.N.G.; supervision, D.P. and R.O.R.. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest

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