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Will Artificial Intelligence Provide Answers to Current Gaps and Needs in Chronic Heart Failure?

Fabiola Boccuto [1], Salvatore De Rosa [1,*], Daniele Torella [2], Pierangelo Veltri [3] and Pietro Hiram Guzzi [4,*]

[1] Department of Medical and Surgical Sciences, Magna Graecia University, 88100 Catanzaro, Italy; f.boccuto@unicz.it
[2] Department of Experimental and Clinical Medicine, Magna Graecia University, 88100 Catanzaro, Italy; dtorella@unicz.it
[3] Department of Computer, Modeling, Electronics and Systems Engineering, University of Calabria, 87036 Rende, Italy; veltri@dimes.unical.it
[4] Department of Surgical and Medical Sciences, University of Catanzaro, 88100 Catanzaro, Italy
* Correspondence: saderosa@unicz.it (S.D.R.); hguzzi@unicz.it (P.H.G.)

Abstract: Chronic heart failure (CHF) is a prevalent and multifactorial condition associated with a significant burden of morbidity and mortality. Despite progress in its clinical management, the projected increase in CHF prevalence due to population ageing, increased cardiovascular risk burdens, and advancing diagnostic and therapeutic options have led to a growing burden on healthcare systems and public budgets worldwide. In this context, artificial intelligence (AI) holds promise in assisting clinical decision-making, especially in analysing raw image data and electrocardiogram recordings. This article provides an overview of the current gaps and needs in CHF research and clinical management and the current and under-development AI-powered tools that may address these gaps and needs.

Keywords: heart failure; artificial intelligence; cardiology; machine learning; neural networks

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Citation: Boccuto, F.; De Rosa, S.; Torella, D.; Veltri, P.; Guzzi, P.H. Will Artificial Intelligence Provide Answers to Current Gaps and Needs in Chronic Heart Failure? *Appl. Sci.* **2023**, *13*, 7663. https://doi.org/10.3390/app13137663

Academic Editor: Laura Cercenelli

Received: 12 April 2023
Revised: 16 June 2023
Accepted: 19 June 2023
Published: 28 June 2023

1. Introduction

Chronic heart failure (CHF) [1] is very common, representing the final evolution stage of several cardiovascular diseases (CVD). Despite the large progress made with its clinical management, CHF is still associated with a large burden of morbidity and mortality [2]. Its pathogenesis is multifactorial, ref. [3] leading to a life-long condition characterised by an increasing hospitalisation rate, with high costs both for the patient and the healthcare system [4]. Moreover, its projected prevalence is expected to steadily increase, due to the improvement in the treatment of cardiovascular diseases and the higher life expectancy of patients [5].

Multiple classifications exist for CHF, based on different elements. According to disease progression, patients can be classified into progressive stages [6], starting from stage A in patients without structural heart disease or symptoms of heart failure (HF), but with a high risk of developing CHF. In contrast, patients in stage B do have structural heart disease but no symptoms of heart failure, yet. Stages C and D are characterised by overt clinical HF increasing severity from C to D. The introduction of stage A highlights the key importance of the early recognition and correction of risk factors, with the aim to prevent the development of CHF and/or the early identification of clinical progression to CHF. This classification is very useful to increase disease awareness and promote early recognition of risk factors and facilitate the identification of clinical signs of progression to a more severe phase of the disease history with the ultimate aim to slow down its course and progression [7]. Using a different approach, the New York Heart Association (NYHA) developed the widespread functional classification stages, based on the severity of symptoms and the level of impairment of physical activities: ranging from NYHA class

I, including patients with no symptoms, nor limitation of physical activity, to NYHA class IV where patients are unable to carry on any physical activity without discomfort and symptoms at rest can be present [8].

The burden of chronic heart failure is continuously growing, and an integrative approach is needed to counteract its impact. On the one hand, CHF is projected to increase progressively: HF currently affects approximately 6 million Americans, with its prevalence projected to increase by 46 per cent by 2030 [9]. The reasons are multiple, including population ageing, increased life expectancy, growing cardiovascular risk burden in developing countries, and improvement in cardiovascular treatments allowing more patients to grow old and eventually develop CHF. On the other hand, advancing diagnostic and therapeutic options brings a progressive increase in healthcare and societal costs, overshooting the current capacity of healthcare systems and public budgets worldwide. Hospitalisations are the most significant component of direct medical expenses that will reach 53 billion dollars in the US [10].

In this context, artificial intelligence (AI) [11] is a promising tool that might positively impact multiple hurdles related to the ever-complicated management of heart failure. With its remarkable ability to analyse large volumes of physiological data obtained from thousands of patients, it can assist clinical practice and decision-making in a much more accurate and selective way than the human brain [12]. AI will be essential in analyzing raw image data from cardiac imaging techniques (such as echocardiography, computed tomography, and cardiac MRI) and electrocardiogram recordings through an algorithm. Multiple AI algorithms are currently able to automatically segment vessels or cardiac structures and to extract useful information, including standard clinical measures and additional indices such as the vessel fractal dimension (FD), capturing the complexity of collateral circulation networks [13–15]. Its adoption in the future will more closely approximate human decision-making, potentially augmenting cardiologists' real-time performance in emergency rooms, catheterisation laboratories, imaging suites, and clinics [16].

Yet, the limits and potentials of AI have yet to be discovered entirely. This article provides an overview of current gaps and needs in CHF research and clinical management, reviewing currently available and under-development AI-based tools that might answer those gaps and need [17] as reported in Figure 1.

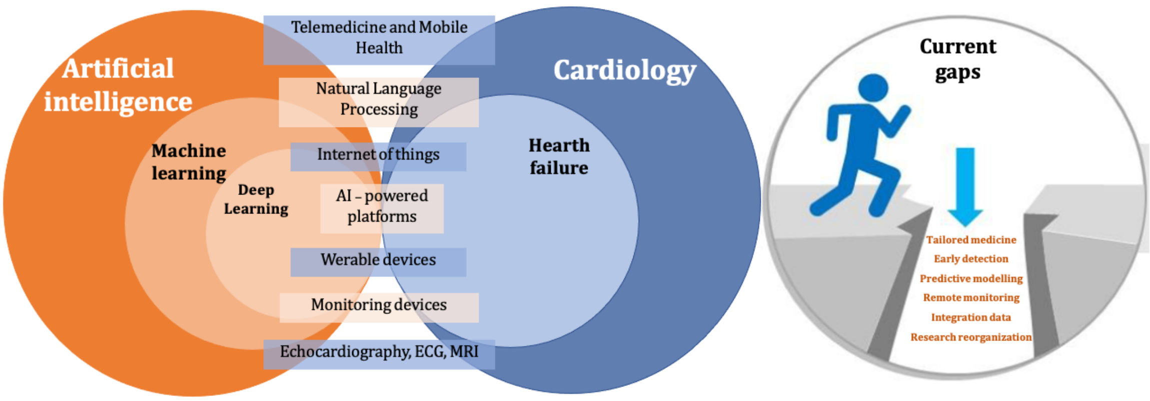

Figure 1. Relationship between artificial intelligence (AI) and cardiology, in particular in the management of heart failure: tools currently available and current gaps. Abbreviations: ECG, electrocardiogram, MRI, magnetic resonance imaging.

The articles and tools mentioned in our work are the results of non-systematic research on currently published literature regarding the use of AI technologies for the management of HF patients. The search was carried out on PubMed, Google Scholar, and Scopus using the keywords: "chronic heart failure", "artificial intelligence", "machine learning", and "deep learning". Well-known studies are also included. All types of articles analyzing the use of artificial intelligence in the management of patients with CHF are discussed.

2. Current Gaps and Needs in Heart Failure Management

This paragraph reviews current gaps in the management of HF patients, to define the most useful application of AI tools. What are the unmet needs of HF management at the current stage?

- Tailored medicine: despite advances in our understanding of the underlying causes of HF, there is still a lack of a truly personalised approach to treatment, taking into account individual factors such as genetics, lifestyle, and disease history [18]. It is essential to define the most appropriate therapeutic strategies depending on patients' comorbidities, the specific etiology of CHF, the patient's lifestyle, and specific disease subgroups (elderly individuals, women, patients with congenital heart disease) [19].
- Early detection: CHF is a chronic, progressive, and irreversible disease. In this context, improving our process for the early detection of HF is of key relevance to improve patient outcomes, especially at early stages [20].
- Remote monitoring: the development of effective and scalable remote monitoring solutions is paramount to improving HF management and reducing hospitalisation rates, with a relevant impact on the control of management costs for healthcare systems and to protect patients' autonomy [21].
- Predictive modelling: to support decision-making and improve patient management, it is advisable to improve the prediction of HF progression and to define the underlying etiologies [22].
- Integration of data: methods for integrating and analyzing large amounts of data from various sources, including electronic health records, imaging, lab results, and wearable devices, to support the diagnosis and management of heart failure are paramount in the current context, where a growing number of clinical data are recorded and stored but often left unused [23].
- Research reorganisation: AI tools could help policy-makers and public payers to improve the prioritisation of research, to better focus on under-investigated and/or most promising topics. As an example, although it is recognised that the microbiome plays an essential role in the pathogenesis of HF, the exact mechanism of action in the development and progression of heart failure is still unknown. Similarly, there is a need to increase research resources on regenerative approaches to HF, including cell-based therapies, gene editing, and tissue engineering, to support the development of new treatments [24].

3. Available AI Resources and Tools

Artificial intelligence (AI) was introduced as an academic discipline in the middle of the 20th Century. AI has gained great attention in recent years due to the introduction of novel algorithms and tools able to solve practical problems in real scenarios, such as clinical and bioinformatics environments [25].

Machine learning (ML) is a field of AI methods allowing computers to learn a task using data without being explicitly programmed. ML methods have been successfully applied in many tasks to integrate heterogeneous data (e.g., analysts, imaging, electronic health records) to discover novel biomarkers [25]. In parallel, ML is deeply applying data-driven science to medical procedures, thus enabling the development of personalised and precision medicine.

More recently, a subset of machine learning called deep learning (DL) has introduced a set of algorithms based on modifying the neural network's architecture. Neural network architecture extends the classical linear perception using non-polynomial activation functions and many hidden layers: the so-called deep neural networks (DNNs). The capability of modelling non-linear tasks has made them extremely popular in both research and application fields concerning a wide range of tasks, with a particular focus on prediction problems.

DL applications have emerged due to the introduction of powerful computing architectures such as graphical processing units (GPUs). Classical applications of DL cover many tasks such as image classification and segmentation, natural language processing, speech recognition, representation learning for graphs, integration, classification, and clustering of heterogeneous biomedical data [26,27].

4. Clinical Applications of AI to CHF Management

Multiple AI-based solutions are currently adopted in all fields of cardiology, such as imaging, invasive monitoring, and remote control of vital parameters, symptoms, or electrocardiography [21].

Current gaps in HF management that AI might fill include early diagnosis and risk prediction through the analysis of electronic health records and data from wearable devices. AI tools can support the early detection of HF and its progression through predictive modelling, remote monitoring, analysis, and interpretation of large amounts of data from various sources, including electronic health records, imaging, and lab results [28]. It may help the development of personalised treatment plans for HF patients based on individual factors such as genetics, lifestyle, and health history. Finally, reminders, alerts, and coaching tools can improve patient adherence to medications and lifestyle changes [29]. Finally, Table 1 summarises some selected tools.

4.1. Telemedicine and Mobile Health

One of the possible applications of AI [30] is in telemedicine and smart-Home technologies. Thanks to remote patient monitoring and management platforms, it is possible to tailor personalised treatment planning, correct drug dosing, and identify patients at risk for adverse events and re-admissions. Among the others, Veta Health [31] is an AI-powered telemedicine platform allowing remote monitoring and management of heart failure patients. As another example, Welby remote monitoring platform uses AI and machine learning algorithms to remotely monitor and manage heart failure patients monitoring their blood pressure levels and achieving weight loss by connecting patients with a clinical care team that can work on nutritional counselling, tracking real-time view of patient blood sugar https://www.welby.care/about accessed on 5 April 2023. According to the World Health Organization (WHO)'s Global Observatory for eHealth, Mobile Health (mHealth) consists of "medical and public health practice supported by mobile devices, such as [cell] phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" http://www.who.int/tb/areas-of-work/digital-health/faq/en/webcite accessed on 5 April 2023. These will offer tremendous potential for monitoring health through phone calls, text messages, data recording, highly portable peripheral devices, and activity monitoring, which may find utility for novel models of health care delivery that are cost-effective, accessible, and patient-centric [32]. Their potential impact is relevant and will be a key tool to complement telemedicine, but will also be a key technology when used together with smart environments and the Internet of Things. MHealth has multiple potential applications. Among the most interesting in CHF is the possibility to track their health by checking their heart rate, blood glucose levels, medication dosages, and sleep cycles. It also allows for remote consultations and maintaining electronic health records [33].

4.2. Monitoring Devices and AI-Powered Platforms

Various devices able to precisely and timely monitor heart failure patients for the early detection of the prediction of clinical worsening are actually available on the market, and many others are under development. Wearable devices that continuously monitor heart rhythm and are already used for detecting atrial fibrillation, such as KardiaMobile by AliveCor [34], and iRhythm Zio XT [35]. In patients with CHF, the impairment of cardiac pumping capacity can cause pulmonary congestion and shortness of breath (dyspnea). This was the drive to develop implantable devices such as CardioMEMS [36] that can measure pulmonary artery pressure (PAP) or devices such as remote dielectric sensing (ReDS) [37] that use electromagnetic waves to detect the extent of pulmonary congestion, which infers lung field concentration, helping in the interpretation of CT scans of lung field concentration. Another device is LINK-HF [38], a non-invasive sensor placed on the patient's chest using adhesive tape able to record ECG, 3-axis accelerometry, skin impedance, body temperature, and posture. Finally, data saved on a cell phone are transferred to an encrypted cloud for viewing and storage. Implantable cardioverter defibrillators offer the opportunity to record and store a number of data which might be well used to increase patients' management. In recent years, a number of algorithms were developed that use data acquired by means of ICD to predict the worsening of HF and the development of acute exacerbations. Among these, the HeartLogic (Boston Scientific, Marlborough, MA, USA), is an automatic, remotely accessible system that combines trend analysis from different sensors, including nocturnal heart rate, acoustic analysis of heart sounds, intrathoracic impedance, respiratory rate, tidal volume, and physical activity, integrating them to generate a single numerical indicator, the HeartLogic index. A significant alteration of the index suggests an acute decompensation of HF. Particularly, an increase in heart rate and a higher intensity of the third heart sound, a decrease in the first heart sound, a higher respiratory rate, a reduction in breathing depth, a diminishing inspiratory volume, a fall in intrathoracic impedance associated with pulmonary congestion, a lower level of physical activity are hallmarks of HF worsening. The system is able to transfer relevant information to a remote monitoring platform that can be accessed by healthcare personnel. The MultiSENSE (Multisensor Chronic Evaluation in Ambulatory Heart Failure Patients) trial enrolled 900 patients with cardiac resynchronisation therapy defibrillators using the HeartLogic model. The algorithm automatically calculated a daily HF index and identified periods as "IN" or "OUT" of an active alert state relative to a configurable threshold. This dynamic assessment can identify patients at increased risk of worsening HF and who, among these, could potentially benefit from early treatment [39]. Along the same line, the MANAGE-HF study enrolled 200 patients implanted with a CRT-D or ICD powered by the HeartLogic algorithm. It demonstrated that the guidance provided by the HeartLogic allowed earlier treatment augmentation, which was then associated with more rapid recovery of the HeartLogic index and of the clinical status of the patient [40]. The utility of the HeartLogic was independently confirmed by Santini et al. The alert system was tested in 104 patients, with the adoption of a standardised protocol including remote data reviews and patient phone contacts every month and at the time of alerts. During a median follow-up of 13 months, the overall number of HF hospitalisations was 16, and 100 alerts were reported in 53 patients. Sixty alerts were judged clinically meaningful and were associated with multiple HF-related clinical conditions [41]. Along the same line, a retrospective analysis by Capucci showed that the HeartLogic algorithm might be helpful to detect the gradual worsening of HF and to stratify the risk of HF decompensation [42]. On the other hand, Treskes et al. evaluated the clinical impact of the HeartLogic algorithm observing a relevant reduction in the total number of HF hospitalisations, which declined from 27 in the pre-activation period to 7 in the post-activation period ($p = 0.003$) [43]. Similar results were reported for the RE-HEART registry: the HeartLogic algorithm was shown to predict HF decompensation or clinically relevant events in more than half of the alerts, with an average of 20 days in advance [44]. The favourable impact of these technologies was also explored in the SELENE HF study, which validated the algorithm HearthInsight for the prediction of heart failure (HF) hospitalisations using remote monitoring data transmitted by implanted defibrillators. The study included patients with an ICD capable of atrial sensing or a CRT-D, left ventricular ejection fraction (LVEF) less than 35 per cent, and a New York Heart Association (NYHA) class II or III before the implantation. All devices used the Home Monitoring technology characterised by daily automatic data transmissions over the Global System for Mobile Communication network. With the developed algorithm, two-thirds of first post-implant HF hospitalisations could be predicted timely with only 0.7 false alerts per patient year [45]. Another platform for HF remote monitoring of implantable devices was tested in the TriageHF, originally developed and validated by Cowie et al. [46] The primary aim of the TRIAGE-HF trial [47] was to correlate cardiac implantable electronic device-generated heart failure risk status (HFRS) with signs and symptoms associated with worsening heart failure (HF). The algorithm could predict the worsening of HF with a sensitivity of 90 per cent. Table 2 summarises these approaches. In the RESPOND-CRT trial, 998 patients were randomised to receive weekly automatic CRT optimisation with SonR vs. an echo-guided optimisation of AV and VV timings. Responder rates were 75.0 per cent in the SonR arm and 70.4 per cent in the Echo arm. At an overall mean follow-up of about 700 days, SonR was associated with a 35 per cent risk reduction in HF hospitalisation [48]. Recent evidence from OptiVol algorithm, available on CRT-D and CRT-P devices was in the PARTNERS HF study that assessed the relationship between OptiVol-powered fluid monitoring data and clinically relevant pulmonary congestion events [49]. Insertable cardiac monitors (ICMs) have become widely adopted in clinical electrophysiology practice. Their utility in the diagnosis of worsening conditions in patients with heart failure was analysed by the LUX-Dx PERFORM, a multicenter, prospective, single-arm, post-market, observational study with a planned enrollment of up to 827 patients, demonstrating the safety of insertion, high data transmission rates, the ability to detect atrial flutter, and the feasibility of remote programming to optimise arrhythmia detection and improve clinical workflow. At the same time, LINQ II ICM enables remote programming capability for all device parameters post-insertion from the clinic, which may reduce patient office visits and scheduling hassles [50]. These algorithm developed to monitor HF might be further improved through AI and/or the integration with other tools, such as CardioMEMS or ReDS, described in Table 1.

Table 1. Selected examples of AI-powered tools and their potential function.

	AI Tools	Function
Telemedicine and Mobile Health	Veta Health	Allow remote monitoring and management of heart failure patients
	Welby	Uses AI and machine learning algorithms to remotely manage heart failure patients monitoring their blood pressure levels and achieving weight loss
Monitoring devices	KardiaMobile	Continuously monitor heart rhythm and are already used for detecting atrial fibrillation
	iRhythm Zio XT	
AI-powered platforms	CardioMEMS	Measure pulmonary artery pressure
	ReDS	Detect the extent of pulmonary congestion
	LINK-HF	Record ECG, 3-axis accelerometry, skin impedance, body temperature, and posture
	Medicomp-Quippi	Help healthcare providers personalise treatment plans and drug dosing
Natural Language Processing	Linguamatics' NLP software	Extract data from electronic health records to provide insights on heart failure patients
	EHR analytics platform	Analyse electronic health records to support the diagnosis and management of heart failure

Table 2. Current algorithms in ICD.

Implantable Devices	Algorithm Name	Type of Device	Function
Boston	HeartLogic	ICD	Reveals signs of elevated filling pressures and weakened ventricular contraction. Measures pulmonary accumulation. Monitors rapid shallow breathing patterns. Indicated cardiac status and arrhythmias. Show activity levels
Medtronic	TriageHF	ICD	Thoracic impedance, detection of arrhythmias, atrial fibrillation burden, evaluation of heart rate, heart rate variability, blood pressure
Biotronik	HeartInsight	ICD	Atrial fibrillation burden, evaluation of heart rate variability, blood pressure, thoracic impedance, detection of arrhythmias,

4.3. Internet of Things (IoT)

The concept of the Internet of Things (IoT) is based on the use of various electronic sensors embedded in objects that are regularly part of our environment by means of a common software platform [51]. From a technical point of view, it consists of three layers; a sensing layer is the patient's particular sensor. A transport layer comprises connectors transporting data from sensors to the remote device; an application layer is a server. IoT has considerable potential for telemedicine and for patients self-monitoring. (Figure 2) Leveraging IoT, physicians can now monitor various vital signs and select clinical parameters to forecast medical emergencies. The most recent technology establishes a global network of machines and gadgets individually equipped with software that allows them to exchange and communicate information through the Internet. The critical feature of IoT is that it can transform anything into an intelligent, bright object by giving it the capacity to act, communicate, sense, and compute.

The application of IoT to smart wearable technology is useful for the management of chronic heart failure patients providing a continuous flow of healthcare data, such as temperature, saturation, cardiac frequency, blood pressure, respiration rate, patient activities, and rhythm abnormalities. This allows early identification of worsening patient status, providing clinicians with a more comprehensive view of a patient's health compared with the traditional sporadic measures captured by office visits and hospitalisations. Several randomised trials have assessed the value of remote non-invasive telemonitoring interventions in HF, with mixed results. For example, one miniature smartwatch-integrated sphygmomanometer (Omron™ HeartGuide) has met the American National Standards Institute criteria for measuring blood pressure by oscillometry across a range of blood pressures. The use of such a wearable device may facilitate optimal adjustment of antihypertensive or heart failure medication, monitoring of iatrogenic hypotension, and support persistence with therapy [52]. A summary of common commercial smart wearables available is available in Table 3 Not only wearable devices are available for remote monitoring and management of patients with heart failure. Platforms like Medicomp Quippi https://medicomp.com/quippe-clinical-data-engine/ accessed on 5 April 2023, Royal Philips' HealthSuite digital platform [53] help healthcare providers personalise treatment plans and drug dosing.

In addition to platforms that facilitate the management of the patient with chronic heart failure, predict tools are able to estimate the risk of developing acute complications, such as the Zebra Medical Vision's Risk Assessment platform http://www.zebra-med.com/ accessed on 5 April 2023, CarePredict's Tempo platform https://www.carepredict.com/ accessed on 5 April 2023. Each platform uses machine learning algorithms to predict the risk of acute clinical complications in heart failure patients based on imaging, electronic health record data and lab results.

Finally, AI tools like Inovalon's AI Risk Assessment platform https://www.inovalon.com/products/the-inovalon-one-platform/ accessed on 5 April 2023, IBM Watson Health's Predictive Analytics platform https://www.ibm.com/topics/healthcare-analytics accessed on 5 April 2023, and Medopad's AI Predictive Analytics platform https://medopad.com/data-and-ai/ accessed on 5 April 2023, predict the risk of developing heart failure based on electronic health record data, lab results, and demographic information [54].

Table 3. Summary of common commercial smart wearables devices and their various cardiovascular clinical applications. BP, blood pressure; ECG, electrocardiogram; HR, heart rate; PPG, photoplethysmography; SaO2, oxygen saturation.

Type of Wearable Device	Sensors	Measurements Available	Clinical Application
Ear buds	PPG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection Long QT diagnosis; HF management; Hypertension screening and management
Smart ring	PPG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Patch	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Chest strap	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Clothing and shoe sensors	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smart watch	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smart band	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smart ring	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management

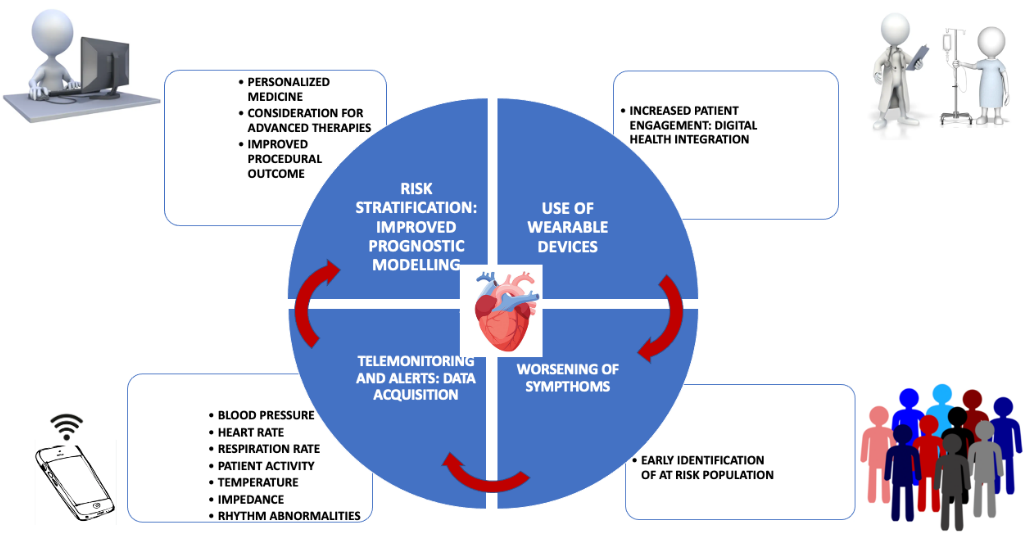

Figure 2. Potential applications of AI-tools to telemedicine. Exemplification case of use of AI-powered tools for the management of HF patients outside the hospital.

4.4. Natural Language Processing

Natural language processing (NLP) refers to the branch of computer science—specifically, the branch of artificial intelligence or AI—concerned with giving computers the ability to understand text and spoken words in much the same way human beings can. NLP combines computational linguistics—rule-based modelling of human language—with statistical, machine learning, and deep learning models. Together, these technologies enable computers to process human language in text or voice data and 'understand' its full meaning, complete with the speaker or writer's intent and sentiment. NLP drives computer programs that translate text from one language to another, respond to spoken commands, and rapidly summarise large volumes of text—even in real-time. Some prominent platforms are the linguamatics' NLP software https://www.linguamatics.com/products/linguamatics-nlp-platform accessed on 5 April 2023, which extracts data from electronic health records to provide insights on heart failure patients; Nuance Communications' Dragon Medical One platform https://www.nuance.com/healthcare/campaign/ppc/dragon-medical-one-solution accessed on 5 April 2023, that enables healthcare providers to document patient information using voice recognition and convert it into structured data. Among the others, the EHR analytics platform from MedAware https://www.medaware.com/ accessed on 5 April 2023, can analyse electronic health records to support the diagnosis and management of heart failure [55]. NLP-based tools might become special tools, particularly for home-based monitoring of CHF patients, for early recognition of clinical worsening. In this context, the patient represents her/his control, and the tool scans the patient's discourse searching for new features that might reflect a reduced functional capacity or a worse clinical condition.

4.5. Application of AI to Echocardiography, ECG, and Cardiac MRI

Applications of AI techniques to electrocardiography, echocardiography, and electronic health records are the most promising. Some experience is already available with CHF patients. The use of AI in echocardiography has been shown to have the potential to mitigate common limitations of this diagnostic technique, such as long execution times with manual measurement of multiple parameters, a high operator subjectivity causing wide observation ranges, and systematic bias [56]. To address these issues, ML models have been trained to recognise specific echocardiographic markers of a wide variety of cardiac diseases helping in the interpretation of data and leading to faster analysis and better outcomes. DL has been mostly utilised in imaging for segmenting the ventricles and evaluating left ventricular ejection fraction (EF), left ventricular volume, left ventricular wall motion function, myocardial contractility, and global longitudinal strain (GLS) [57]. Another good example of the application of DL to echocardiography is the possibility to automatically annotate and classify both 2D and Doppler tracings with excellent performance (AUC = $0.90 - 0.92$ to detect a left ventricular ejection fraction) [58]. Another use of ML in this field is with cardiac MRIs, generating segmentations of heart chambers that yield imaging biomarkers to predict CHF with an excellent reconstruction accuracy both for the right ventricle and for calculation of left ventricular mass, papillary muscle identification, common carotid artery, and descending aorta measurements [16]. Interpretation of multiple features on ECG tracings also presents some hurdles. In this regard, an AI-powered platform for the analysis and interpretation of ECG data, thanks to ML models, has recently been shown to help reduce the time taken in diagnosis to recognise the patient to send to urgent care quickly. A similar AI tool enables the use of ECG as a screening tool (e.g., to predict heart failure in asymptomatic individuals or the worsening in patients with an established diagnosis) learning from big data sets, without the need to understand the biological mechanism [59]. An example is Cardiogram's DeepHeart platform [60], an AI-powered platform that uses machine learning algorithms to detect ischemic heart failure from ECG data. Artificial-intelligence-powered algorithms can be very practical in analysing long EKG recordings, which would otherwise be very demanding. In fact, the improvements in wearable technologies make it nowadays possible to register continuous EKG tracings for several days up to some weeks [61]. Without an AI-based analysis, it would not be possible for healthcare personnel to analyse the complete tracings [62,63]. Harmon DM et al. demonstrated an excellent predictive capacity (AUC = 0.903) using electrocardiograms to detect left ventricular systolic dysfunction across age and ethnic subgroups [64]. Cardio-HART is an AI-powered, cardiac diagnostic system for use in clinical care settings, including primary and secondary care. It starts in a clinical care setting where the CHART device first captures the biosignals, ECG, phonocardiography (PCG), and mechanical force bio-signal (MCG), and then uploads them to the cloud for AI processing [65]. The CHART AI then outputs a wide range of medical findings or endpoints, consistent with cardiac dysfunction. In particular, Cardio-HART can diagnose 14 HART-findings—including structural, functional, and valve problems, that are classified as "Normal/Mild/Abnormal". From these HART findings, HF is then classified into four phenotypes, consistent with their medical context: HF unlikely, HFpEF, HFmrEF, and HFrEF. HART-findings were validated with a database having both parallel bio-signals and ECHO assessment. Cardio-HART HF prediction reaches significantly higher overall performance compared to the best ECG criteria, with a sensitivity of 83 per cent, specificity of 87 per cent and a positive predictive value of 70 per cent. CHART has the potential to enable effective widespread screening of patients for the early detection of CVD onset and resolve many 'inconclusive ECG' results, thereby reducing time in referral decisions [66]. Along the same line, in a recent retrospective study, the authors developed novel machine learning (ML) models to predict HF-related mortality, incorporating social determinants of health. In this study, the AI-powered tool outperformed traditional logistic regression models for prognostic prediction [67].

5. Smart Clinics

Smart clinics can be defined as medical institutions that create new value and insights on patient safety, quality of care, and cost-effectiveness using information and communications technology. The main services of smart clinics are the Internet of Things (IoT), mobile health, AI, robotics, extended reality, high-speed communication networks, and telehealth. Thanks to these it will be possible to improve the efficiency of integrated nursing care services but also treatment, education, and training in medical institutions. With the introduction of smart clinics, preventive health management is provided in various living spaces of local communities, such as homes and workplaces, using mobile and wearable sensors, which is expected to achieve customer-centred medical services that can be accessed from the comfort of people's residences through the virtual expansion of hospitals without physical space restrictions. In addition, based on the data collected through smart hospitals, specific detailed indicators related to the core aspects of medical value can be defined, quantitatively measured, and fed back to inform healthcare policy. Data collected through smart hospital services within medical institutions will contribute to the establishment of national healthcare policies by defining and quantitatively measuring detailed indicators related to core aspects of medical value. This "virtual expansion of hospitals" will contribute to the realisation of customer-oriented medical services that individuals encounter in their daily lives.

6. Current Research Focus

Current healthcare research is strongly focused on the concept of personalisation and early prevention. In this context, AI can be a powerful tool for predictive modelling, e.g., through deep learning. A key challenge for the near future will be the development of lean, efficient, and highly integrated algorithms to improve the management of the patient with CHF, particularly to predict the risk of developing heart failure or its progression [68]. The added value of AI tools in this setting resides in (i) the efficiency of execution, (ii) the ability to measure and recognise additional pieces of information that are currently underestimated and/or under-recognised by human examiners, and (iii) their reproducibility. Wearable devices and remote monitoring will change the management of these patients, allowing a higher degree of personalisation, taking into account multiple individual characteristics such as genetics, lifestyle, and health history. Some of the ongoing projects are the AI-Powered Heart Failure Management System (AIHFMS) [16], and The Heart Failure Prediction with Deep Learning project [69], which aim at developing a deep learning algorithm to predict the risk of heart failure progression based on electronic health record data and wearable device data and based on imaging and lab results respectively [22]. Another example is the Cardihab project, a digital health platform developed by researchers at the University of Sydney that uses AI to personalise heart failure management. The platform tracks patients' symptoms, medication adherence, and lifestyle habits and uses AI algorithms to provide personalised feedback and treatment recommendations. https://cardihab.com/ accessed on 5 April 2023. In the meantime, the Personalized Heart Failure Management with AI project will develop a personalised treatment plan for heart failure patients based on individual factors such as genetics, lifestyle, and health history. Another promising project is the continuous monitoring of patient devices in critical scenarios, such as for example the coaxial intraventricular pump, supporting the circulation in patients with severe failure of cardiac function. As an example of how this technology might be used in future clinical practice, Abiomed has already trained an AI algorithm to predict the next five minutes of a patient's arterial pressure based only on the prior five minutes of console data and has also developed AI algorithms to predict other parameters, such as stroke volume, left ventricular pressure and cardiac output. (https://www.abiomed.com/about-us/news-and-media/press-releases/fda-approves-data-streaming-impella-console-setting-stage-artificial-intelligence accessed on 5 April 2023, ref. [70] Among the major randomised trials, the TIM-HF2 trial evaluated the usefulness of a multicomponent system comprising a three-channel ECG, in HF patients with NYHA class II–III and a left ventricular ejection fraction (LVEF) under 45 per cent (PhysioMem PM 1000, GETEMED Medizin und Informationstechnik AG, Germany), a BP device, a weight scale, and an oxygen saturation device. The intervention, compared with usual care, was associated with an improvement of the clinical condition, measured as a lower number of days lost from unplanned HF-related hospital admissions and had lower all-cause mortality (HR 0.70, 95 per cent CI 0.50–0.96) [71]. The TEMA-HF1 trial demonstrated that the use of telemonitoring during follow-up in patients with HF reduced all-cause mortality (an absolute reduction of 12.5 per cent), with a lower number of follow-up days lost to death, hospitalisation, or dialysis [72]. Interesting results are those coming from a study by Gelman et al., which demonstrated that the randomisation of diuretic regimens guided by a second-generation personalised AI algorithm improves the response to diuretic therapy with a significant reduction in NT-proBNP and serum creatinine values [73]. Therefore, a novel, machine learning-derived model was validated also by Segar et al. to predict the risk of heart failure (HF) among patients with type 2 diabetes mellitus (T2DM). The cumulative 5-year incidence of HF increased in a graded fashion from 1.1 per cent in patients with WATCH-DM score of 7 to 17.4 per cent in patients with a WATCH-DM score of more than 14 [74]. Among ongoing studies, HeartMan project aims to develop a personal health system that would comprehensively address CHF self-management by using sensing devices and artificial intelligence methods with significantly improved self-care behaviour and reduction of depression and anxiety [75]. The role of deep-learning-based echocardiography in the diagnosis and evaluation of the effects of routine anti-heart-failure Western medicines was investigated in elderly patients with acute left heart failure (ALHF). The study demonstrated a reduction in rehospitalisation and mortality rate [76].

7. Limitation

Since AI is a "newborn", rapidly evolving topic, some limitations can be identified. First, a standardised protection system that guarantees the security and privacy of patients' data is strongly needed. Second, the application of AI-powered technologies is not within reach of all patients. As a matter of fact, there are still remarkable differences in internet services and technological deficiencies among the various countries. Moreover, there is great heterogeneity in technological adherence from both patients and caregivers. From a perspective view, AI tools should be available for the entire population, without socio-economic distinctions. Third, data about the application of AI in CHF mostly derives from observational studies, whereas randomised controlled trials (RCTs) are still scanty. In addition to scientific evidence, some ethical issues still need to be fully addressed. For example, some AI-computational models imply the use of an inscrutable layer of analysis, also known as the "black box", which represents a source of ethical concern. A further issue is the need for cross-speciality education and training to promote technical knowledge among healthcare personnel and healthcare literacy among AI experts.

8. Future Perspectives

Artificial intelligence will dramatically improve the usefulness of new and upcoming "smart" technologies, such as wearable devices, mobile health, and a number of different sensors. Leveraging on a large amount of reliable and precise data AI algorithm will process these data together with other data obtained through traditional methods (anamnesis, clinical reports, medical examination, subject's history) to obtain a more precise and reliable diagnosis and prognostic prediction, allowing a truly tailored approach to therapy. Multiple applications can be envisioned, ranging from health risk assessment for the development of heart failure, continuous monitoring of the health status and state of progression of CHF, smart interactive planning of clinical visits and examinations, early recognition of "red flags" announcing acute complications, prediction of the likelihood of responding to a particular treatment, and many more. Foremost, the new avenues opened up by the new possibilities brought about by AI solutions will need a change in our paradigm of clinical research, shifting from research models focused on testing a single experimental intervention to the utilisation and evaluation of protocols and approaches to a specific health issue. This would put the patients at the centre of focus and will allow us to evaluate truly personalised interventions. Integrating multiple data sources will allow a holistic view, data standardisation and real-time monitoring of heart failure patients, enabling early detection of changes in health status and triggering early intervention. Finally, AI tools will be very helpful to support the discovery and development of new therapies for heart failure, improving our understanding of the underlying mechanisms of the disease, and integrating large amounts of data from various sources. AI-powered tools will drive a dramatic improvement of in silico tools in drug development research.

Author Contributions: Conceptualisation, F.B., S.D.R. and P.H.G.; methodology, F.B. and P.H.G.; resources, P.H.G.; writing—original draft preparation, F.B., S.D.R. and P.H.G.; writing—review and editing, D.T. and P.V.; visualisation, F.B., S.D.R., D.T., P.V. and P.H.G.; supervision, S.D.R., D.T., P.V. and P.H.G.; project administration, S.D.R. and P.H.G.; funding acquisition, P.H.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by grants from the Italian Ministry of University and Research (PNRR-National Center for Gene Therapy and Drugs based on RNA Technology—CN00000041), and from the Italian Ministry of Health (PSC SALUTE 2014-2020 -POS4 "Cal-Hub-Ria"-T4-AN-09 and PNRR-MAD-2022-12376814). P.V. and P.H.G. were supported by a grant from the Italian Ministry of Enterprises and Made in Italy (MISE): PON-VQA.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing is not applicable to this article. In fact, no new data were created or analysed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
CHF	Chronic Heart Failure
CVD	Cardiovascular Diseases
NYHA	New York Heart Association
HF	Hearth Failure
AI	Artificial Intelligence
FD	Fractal Dimension
ML	Machine Learning
DL	Deep Learning
GPUs	Graphical Processing Units
mHealth	Mobile Health
PDAs	Personal Digital Assistants
PAP	Pulmonary Artery Pressure
ReDS	Remote Dielectic Sensing
IoT	Internet of Things
NLP	Natural Language Processing
SM	Self Management
EF	Ejection Fraction
GLS	Global Longitudinal Strain
CHART	Cardio-HART
PCG	Phonocardiography
MRI	Magnetic Resonance Imaging
MCG	Mechanical Force Bio-signal
HFpEF	Hearth Failure with Preserved Ejection Fraction
HFmrEF	Hearth Failure with Midly Reduced Ejection Fraction
HFrEF	Hearth Failure with Reduced Ejection Fraction
ECG	Electrocardiogram
DNNs	Deep Neural Networks
ICMs	Insertable cardiac monitors
ICD	Implantable Cardiac Defibrillator
AIHFMS	AI-Powered Heart Failure Management System
MultiSENSE	Multisensor Chronic Evaluation in Ambulatory Heart Failure Patients
HFRS	Heart Failure Risk Status

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