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Research paper

Artificial intelligence: Applications in cardio-oncology and potential impact on racial disparities

Gift Echefu [a], Rushabh Shah [b], Zanele Sanchez [c,d], John Rickards [e], Sherry-Ann Brown [f,g,h,*]

[a] Division of Cardiovascular Medicine, University of Tennessee, Memphis, TN, USA
[b] Medical College of Wisconsin, Milwaukee, WI, USA
[c] School for Advanced Studies, Miami, FL, USA
[d] Miami Dade College, Miami, FL, USA
[e] Mercer University School of Medicine, Macon, GA, USA
[f] Department of Medicine, Medical College of Wisconsin, Milwaukee, WI, USA
[g] Department of Cardiovascular Medicine, Mayo Clinic, Rochester, MN, USA
[h] Heart Innovation and Equity Research (HIER) Group, Miami, FL, USA

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ABSTRACT

Numerous cancer therapies have detrimental cardiovascular effects on cancer survivors. Cardiovascular toxicity can span the course of cancer treatment and is influenced by several factors. To mitigate these risks, cardio-oncology has evolved, with an emphasis on prevention and treatment of cardiovascular complications resulting from the presence of cancer and cancer therapy. Artificial intelligence (AI) holds multifaceted potential to enhance cardio-oncologic outcomes. AI algorithms are currently utilizing clinical data input to identify patients at risk for cardiac complications. Additional application opportunities for AI in cardio-oncology involve multimodal cardiovascular imaging, where algorithms can also utilize imaging input to generate predictive risk profiles for cancer patients. The impact of AI extends to digital health tools, playing a pivotal role in the development of digital platforms and wearable technologies. Multidisciplinary teams have been formed to implement and evaluate the efficacy of these technologies, assessing AI-driven clinical decision support tools. Other avenues similarly support practical application of AI in clinical practice, such as incorporation into electronic health records (EHRs) to detect patients at risk for cardiovascular diseases. While these AI applications may help improve preventive measures and facilitate tailored treatment to patients, they are also capable of perpetuating and exacerbating healthcare disparities, if trained on limited, homogenous datasets. However, if trained and operated appropriately, AI holds substantial promise in positively influencing clinical practice in cardio-oncology. In this review, we explore the impact of AI on cardio-oncology care, particularly regarding predicting cardiotoxicity from cancer treatments, while addressing racial and ethnic biases in algorithmic implementation.

1. Introduction

Cancer patients at risk of cardiotoxicity must be identified to improve oncologic and cardiovascular outcomes. In-depth characterization of these patients could help specify those in need of increased monitoring to allocate resources more effectively. There is growing evidence that AI algorithms can accurately forecast patients more likely to develop cardiovascular complications and improve detection using currently available cardiovascular clinical and imaging data [1]. The advancement and adoption of precision medicine, AI, and machine learning (ML) in medicine, presents the prospect for more precise and personalized strategies in the management of cancer related cardiac dysfunction and could analyze patterns from inputted data to forecast new references (Fig. 1). Imaging is conducted at various intervals during the treatment continuum, providing clinically relevant data that can be integrated into AI algorithms for precise cardio-oncology care. Extensive multicenter national and global imaging databases have been established, consisting of imaging data formatted for seamless integration

* Corresponding author at: Department of Medicine, Medical College of Wisconsin, 8701 Watertown Plank Road, Milwaukee, WI 53226, USA.
E-mail address: shbrown@mcw.edu (S.-A. Brown).
@drbrowncares (S.-A. Brown)

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into ML algorithms [2,3]. The application of AI-augmented cardiac imaging in cardio-oncology is gaining popularity. A considerable number of cardio-oncology patients undergo screening and are evaluated based on left ventricular ejection fraction (LVEF) and global longitudinal strain (GLS), obtainable by echocardiography. AI is being applied to improve the precision, efficiency, and accuracy of LVEF and GLS, to drive point-of-care image acquisition, and to combine imaging and clinical data to maximize cardiac dysfunction prediction and diagnosis. Furthermore, AI is being explored for the forecasting and evaluation of cardiac tumors and cardiovascular complications in patients treated for childhood or adult cancer using cardiovascular magnetic resonance imaging (MRI), computed tomography (CT), single proton emission computed tomography (SPECT), and positron emission tomography (PET) [4].

In the United States, disparities exist in the health outcomes of racial and ethnic minorities. These inequalities are a driven by unequal access to healthcare services and the influence of social and economic factors (Fig. 2). Considering the significant healthcare gap among marginalized communities, advancements in medical research, including the development of novel medications and treatments, may not lead to improved health outcomes for all populations. However, access to these therapies is often limited by a lack of diversity in clinical trials, restricted care access, insufficient cultural competency and financial disenfranchisement [5]. Additional social determinants centered around technology, coupled with existing health disparities, can lead to further inequity (Fig. 2). Systematic flaws in AI systems give certain individuals or groups unfair benefits or disadvantages, propagating "algorithmic bias" [6]. As a result, the insufficient representation of minority and underrepresented groups in clinical datasets utilized by AI algorithms may limit their capacity to generate trustworthy predictions.

AI is also advancing in the realm of digital technology and patient monitoring, including devices like blood pressure and heart rate monitors, pulse oximeters, and glucose monitors. These AI-powered remote monitoring devices can be integrated with telemedicine to enhance healthcare access for patients in underserved areas [7]. Additionally, AI may enhance cardio-oncology care by integrating with digital health tools and EHRs, potentially enabling more timely and precise interventions [8]. However, these AI models must be trained on unbiased datasets to prevent the exacerbation of existing inequities. As such, AI holds the potential to impact several avenues within cardio-oncology.

2. AI models for predicting risk of cancer therapy related cardiac dysfunction

Cancer-related cardiovascular complications are the leading cause of death among cancer patients and survivors, second only to recurrence [9]. It is estimated that over 370,000 cancer survivors die from cardiovascular complications each year [10]. Cancer patients and survivors are adversely affected by several current and emerging cancer therapies. Broadly defined, cardiotoxicity refers to any "toxicity that affects the heart", according to the United States National Cancer Institute [11]. Alterations in the LVEF are included in more precise clinical definitions of cardiotoxicity to include a decrease of LVEF by 10 % or a value below 53 % [12]. There is clinical and scientific evidence that cardiotoxicity transcends the effects of anthracyclines and radiation-induced cardiomyopathies [13,14]. Anthracyclines are the most commonly studied chemotherapeutic agents closely tied to cardiomyopathy, yet many new cardiotoxic pharmacological agents have been linked to cardiovascular effects, including endocrine therapies and targeted therapies [9,15,16]. About a third of cardiovascular disease in cancer patients can be attributed to toxicity caused by anticancer therapies including chemotherapy, targeted therapies, immunotherapies and radiotherapies [17]. While the majority of these complications are immediate or subacute, certain therapies can result in cardiotoxic events that occur even decades after the termination of cancer therapy. The risk of cardiovascular toxicity varies throughout the cancer process and is affected by multiple factors, including age, gender, genetics, prior cancer and cancer treatments, baseline cardiovascular risks and diseases, type, and duration of cancer therapies [18]. To improve oncologic and cardiovascular outcomes, it is essential to identify individuals at risk of cardiotoxicity from cancer treatments [19]. On this basis, cardioprotective approaches can be implemented and therapies modified. A comprehensive characterization of this vulnerable group could identify individuals requiring more rigorous surveillance for effective resource allocation.

There are a few risk-assessment and prediction tools that are either being developed or currently available to clinically determine those at high risk and guide care. The European Society of Cardiology (ESC) guidelines recommend using the Heart Failure Association (HFA) and International Cardio-Oncology Society (IC-OS) baseline risk stratification score in the management of cardio-oncology patients [20,21]. The scoring tool was designed based on relevant literature and evaluates potential cardiotoxicity of seven categories of cancer treatments:

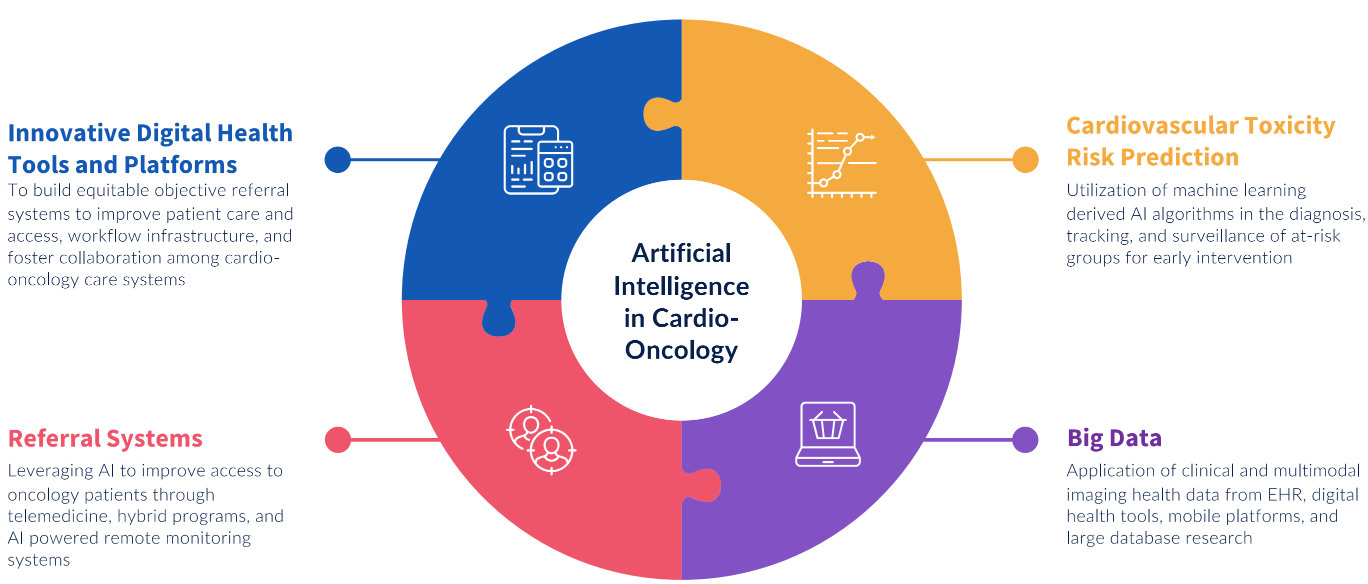

Fig. 1. Avenues for clinical application of artificial intelligence in cardio-oncology. These avenues are solutions to addressing racial/ethnic health disparities. Adapted with permission from [108]. AI: artificial intelligence, EHR: electronic health record.

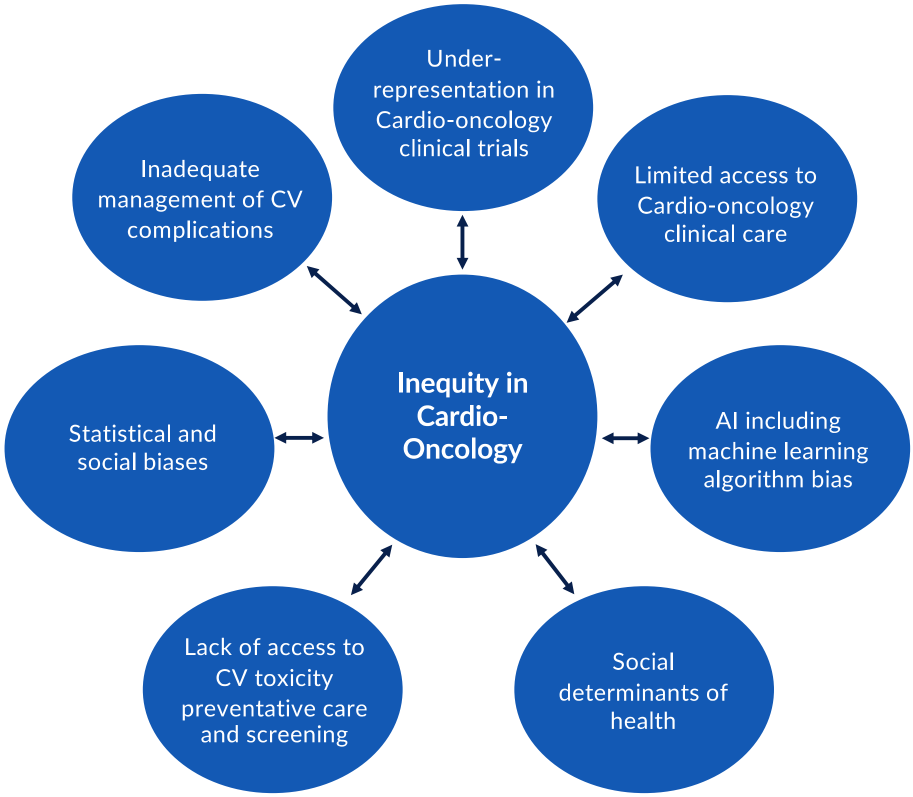

Fig. 2. Factors contributing to inequity in cardio-oncology. Adapted with permission from [72]. AI: artificial intelligence, CV: cardiovascular.

anthracycline chemotherapy, HER2 (human epidermal growth factor receptor 2) targeted treatments, vascular endothelial growth factor inhibitors, second and third generation BCR-ABL (Breakpoint cluster region- Abelson proto-oncogene), multi-targeted kinase inhibitors, proteasome inhibitors, RAF (rapidly accelerated fibrosarcoma) and MEK (mitogen-activated extracellular signal-regulated kinase) inhibitors, and androgen deprivation therapies for prostate cancer. Prospective validation studies on real-life baseline risk stratifications of specific cancer populations such as breast and hematological cancers are ongoing [22,23]. However, the ESC Pocket Guidelines Application is available for clinical use. Patients should undergo electrocardiogram (ECG) assessment prior to treatment with known cardiotoxic therapies. Further, guidelines for cardio-oncology have also set precise recommendations for assessing cardiac biomarkers and baseline transthoracic echocardiography (TTE) based on cancer treatments and baseline estimated HFA-ICOS risk scores [20]. These models alongside clinical and imaging data can be integrated into patients' EHR platforms to automate the referral process and foster timely intervention.

AI algorithms have been demonstrated to effectively predict patients at risk of cardiac complications and to enhance detection based on routine cardiovascular data [1]. Despite societal guideline recommendations and expert opinions, risk assessment and management strategies remain fragmented and mostly subject to interpretation and implementation at the discretion of the provider. AI and innovative health tools could bridge these gaps and automate the risk assessment process. By combining specialized real-world patient data sets with other clinical information, including genomics, proteomics, cardiac imaging variables, ECG, cardiac biomarkers, and unstructured medical documentation, computer models can assist researchers in addressing research questions about cancer therapy related cardiac dysfunction by providing insights derived from data [24]. The integration of AI into cardiovascular medicine will aid in providing personalized and precise patient care. In AI, computer systems use imputed data to simulate human intelligence. ML and deep learning (DL) approaches applied to a variety of cardio-oncology features can revolutionize prediction and diagnosis. AI tools, through ML, can learn patterns from imputed data to predict new references. Using empirical data, supervised ML algorithms are trained to create models capable of predicting future events. Random Forest and Artificial Neural Network algorithms may be applied to develop predictive risk score models for cancer therapy related cardiac dysfunction [25]. ML relies on algorithms' capability to handle diverse data in a learning set to produce precise and reliable forecasts [26]. A dataset that has not been encountered previously should be used to validate the algorithm's performance [27]. Area under curve (AUC) or C-statistics are often used to assess the model's ability to distinguish between outcomes, as well as calibrating the model-derived risk estimate to the observed outcomes [28]. Natural language processing provides the AI systems with the ability to interpret, manipulate, and translate data based on the provided algorithm. In ML, the input dataset is separated into three subsets: the training set, the test set, and the validation set. The entire dataset utilized in the training set is extensive and employed for the development of the ML model. Test sets are utilized to evaluate a model's performance and fine-tune its parameters. The created ML model is assessed for its overall performance by feeding it validation sets, typically consisting of unknown samples [29].

The described process of modeling in ML is outlined as follows: (I) The necessary data for constructing the model are acquired from an electronic health record system, laboratory parameters, and imaging data. The collected data are then preprocessed to remove any invalid data. (II) Conventional statistical approaches, such as conventional linear regression analysis or ML algorithms, are employed to identify independent variables that have a significant impact on the outcome variables. Relevant guidelines or clinical expertise are utilized to determine the appropriate predictors. (III) A ML algorithm is chosen based on the data's properties, and a corresponding ML model is built. (IV) The ML model is then validated, and the sensitivity, specificity, and AUC of the model are determined to assess its performance [30].

A prediction model is a mathematical model that must have the ability to distinguish individuals into groups, rank individuals based on their likelihood to belong to a group or estimate the probability of belonging to a certain group. Several statistical approaches to prediction exist with their unique characteristics, advantages, and limitations [31]. Therefore, clinicians should know how and when to incorporate AI risk prediction models into clinical practice. This is specifically in terms of which algorithms are most creative, explicable, easily adapted, and should be embraced. Features to consider prior to implementing a predictive model into clinical practice include its ability to discriminate between outcomes of interest (e.g. all diseased or non-diseased), risk calibration (how accurate are the risk estimates compared to the actual risk), confidence intervals, model validation methodology and generalizability (the results should be applicable to intended patient demography) [32].

A recent study evaluated the prevalence of late-onset cardiomyopathy in pediatric cancer survivors using an AI-assisted risk prediction tool [33]. The authors applied AI tools to 10-second 12-lead ECGs derived from 1217 cancer survivors in the prospective St. Jude Lifetime Cohort (SJLIFE) study. The study found that combining clinical and ECG characteristics accurately predicted (78 %) those who had cardiomyopathy and excluded those who did not, with positive and negative predictive values of 30 % and 97 %, respectively, and an AUC of 0.89 (95 % confidence interval [CI]: 0.86 to 0.91). Similarly, the use of AI models was effective in predicting cardiovascular disease risks among adult cancer survivors in a large institutional study [34]. This study examined a longitudinal cohort of 4309 cancer patients (with up to 22 years follow up data) at the Cleveland Clinic with six cancer therapy-related cardiovascular toxicities including atrial fibrillation, coronary artery disease, heart failure, myocardial infarction, stroke, and de novo cardiovascular toxicities. A ML model was built using individual patient characteristics, cancer type, choice of treatment (chemotherapy and radiation), and clinical variables (laboratory tests and echocardiographic variables). Logistical regression had the best performance among the several ML algorithms systematically evaluated. Incorporating both echocardiographic and laboratory data improved the model's performance. Again, the ML model indicated high generalizability in predicting cancer related cardiotoxicities when applied to time-split data to simulate real-world scenarios [34].

3. AI-based risk prediction utilizing cardiovascular imaging

Medical AI applications are rapidly advancing and transforming clinical practice, particularly in identifying established data trends and predicting new outcomes. AI-guided cardiovascular image analysis can accurately, reliably, and affordably identify and quantify cardiovascular risks, thereby aiding in improved detection strategies, which could provide efficient preventive and therapeutic opportunities in cardio-oncology [35]. Cardio-oncology imaging data sets can be used as predictive instruments but have not been widely applied. A rapid advancement in sophisticated multimodal cardiovascular imaging has generated significant amounts of data that have revolutionized cardiovascular care [1]. Throughout treatment, imaging is performed at various stages in the care of cancer patients. Therefore, multiple opportunities exist for implementing AI and imaging in predicting those at high risk of cardiac dysfunction prior to therapy, in those with evolving cardiac dysfunction during therapy, in those with subclinical cardiac dysfunction, and in those who will develop long-term toxicity (Table 1). In cardiovascular care, large multicenter national and global imaging databases have been developed, consisting of imaging data processed in formats that are easy to integrate into ML algorithms [2,3]. Despite this, assessment and clinical application of many imaging variables in cardiovascular medicine remain limited by subjective visual assessments made by the interpreter [1].

Echocardiograms and other medical data are abundant with imaging indicators that can be used by AI to create novel functional indices and possibly enhance diagnosis and prognostic accuracy. A TTE is vital in cardio-oncology for assessing cardiac structure and function, identifying and monitoring cardiotoxicity resulting from cancer therapies with particular focus on LVEF and GLS [36,37]. The use of AI can enhance prognostic and diagnostic outcomes by detecting subtle abnormalities in baseline echocardiograms that would have gone undetected with current techniques [21,38]. Using >2.6 million echocardiogram images from 2850 patients, a deep learning model (EchoNet) was built to identify local cardiac structures, estimate cardiac function, and predict systemic phenotypes that modify cardiovascular risk [39]. The study participants were majorly non-Hispanic whites (58 %) with 42 % racial and ethnic minorities consisting of 14 % African American, 12 % Hispanic, 8 % Asian, with 0 % [14,8] Pacific islander and American Indian. The EchoNet algorithm accurately identified left atrial enlargement, left ventricular hypertrophy, left ventricular end-systolic and diastolic volumes, and LVEF. Additionally, it predicted phenotypic data such as age, gender, weight, and height [39]. In a prospective cohort study of 248 breast cancer patients who received 240 mg/m2 of doxorubicin chemotherapy, supervised ML algorithms were applied to identify the echocardiographic strain features that were most significantly linked to cardiotoxicity in the participants [40].

In another study, assessment of 615 echocardiograms found that the

Table 1
Artificial intelligence imaging applications in clinical practice. Adapted with permission from [4].

Treatment stages	Imaging type	Benefit	Implementation
Pre-treatment (determine pre-existing cardiovascular condition)	- Echo: initial baseline echo with LVEF and GLS - SPECT: high risk patients - CMR characterization - PET: to determine baseline detection of microvascular and macrovascular damage - Coronary artery calcium scoring on chest CT	- Improved diagnostic and predictive accuracy Improved outcomes - Better prediction of short- and long-term outcomes	-Development of patient friendly interfaces for shared decision making and support
During treatment (determine evolving cancer therapy-related cardiac dysfunction)	- CMR characterization - FDG-18 PET for patients managed with ICIs - Serial echocardiography - PET for the detection of microvascular and macrovascular damage	- Improved diagnostic and predictive accuracy Improved outcomes - Better prediction of short and long-term outcomes	Development of patient friendly interfaces for shared decision making and support
After treatment (long term surveillance for cancer related cardiovascular injury)	- Reassess heart function- echocardiography with LVEF and GLS - Chest CT for cancer surveillance and coronary calcium scoring - PET for detection of microvascular and macrovascular damage - CMR characterization - SPECT in high-risk patients	- Improved diagnostic and predictive accuracy Improved outcomes - Better prediction of short- and long-term outcomes	Development of patient friendly interfaces for shared decision making and support

CMR: cardiac magnetic resonance, FDG: fluoro-deoxy-glucose, GLS: global longitudinal strain, ICI: immune checkpoint inhibitors, LVEF: left ventricular ejection fraction, MRI: magnetic resonance imaging, PET: positron Emission tomography, SPECT: single photon emission computed tomography.

correlations between baseline segmental and global strain echo features and subsequent decreases in LVEF declined over time. Features that strongly associate with subsequent declines in LVEF are mid-septal and anteroseptal left ventricular (LV) segmental strain, and strain rate in both circumferential and longitudinal dimensions, as well as average longitudinal strain. However, it is relevant to note that this pilot work needs further study, as associations between segmental strain features and LVEF declines are not yet well studied. AI algorithms may therefore be detecting predictive features on strain which are not well recognized and may warrant further investigation. A meta-analysis explored the prognostic value of GLS measurement in predicting cardiovascular toxicities following chemotherapy with anthracyclines with or without trastuzumab. Study results indicate that GLS measured after treatment initiation has a strong prognostic value for subsequent cancer therapy-related cardiovascular toxicities. The study results require further validation through prospective studies due to data heterogeneity, publication bias, and limited GLS data [38].

Though the echocardiogram is the most utilized imaging technique for the diagnosis of cardiomyopathy, an electrocardiogram is easily obtainable as a diagnostic tool in noncancer and cancer patients. ECG data has been available for the diagnosis of certain cancer therapy-related cardiovascular toxicities since the 1970s. Changes in the different intervals and complexes have been associated with cardiomyopathy from anthracycline therapy dating back to 1977 [41]. AI algorithms utilizing 12-lead ECGs (termed here as "AI/ECG") have demonstrated the ability to forecast several cardiac conditions, including heart failure with reduced left ventricular ejection fraction, susceptibility to atrial fibrillation while in normal sinus rhythm, left ventricular hypertrophy, and coronary artery disease in non-cancer patients [42–46]. Findings of a large institutional study based solely on electrocardiogram data showed that ECG based AI algorithm predicted heart failure with comparable accuracy to existing Framingham Heart Study (FHS) and Atherosclerosis Risk in Communities (ARIC) risk calculators [47]. A study analyzed >1 million 12-lead ECGs and clinical information from over 415,000 patients to forecast atrial fibrillation [48]. The recordings were categorized by class, age, and gender and assigned to training, validation, and test sets. Based on a given recording, a ML classifier was trained to predict the likelihood of developing atrial fibrillation (AF) within a five-year period. According to the study, the most accurate predictions were obtained when variables like heart rate variability and ECG morphology were combined with demographics, clinical data, and designed features (AUC = 0.91). Although not specifically focused on cancer survivors, the aforementioned studies demonstrate potential for implementation in cardio-oncology. Specific to cardio-oncology, the TACTIC trial (ClinicalTrials.gov Identifier: NCT03879629) is investigating the use of AI/ECG to identify cancer patients and survivors at risk of cancer therapy-induced cardiomyopathy. This trial aims to determine the necessity, timing, and duration of cardiac protection using carvedilol, a beta blocker in breast cancer patients undergoing HER2-targeted therapy. Another study objective is to assess in patients receiving HER2-directed therapies the performance of an AI/ECG algorithm built and validated to identify LVEF of 35–40 % in the general population.

A cardiac magnetic resonance (CMR) imaging study can detect myocardial changes related to myocarditis with high accuracy [49]. Myocardial strain can be evaluated using novel techniques such as feature tracking, tagging, and fast-strain-encoded CMR [50]. CMR has been analyzed using deep learning algorithms to accurately and automatically estimate LV volumes and function [51]. An AI model could automate the detection of cardiac pathology and cardiotoxicity in cardio-oncology, but further studies are needed [4]. Detection of initial signs of subclinical myocarditis has been achieved using artificial intelligence models. In a study, artificial intelligence algorithms were applied to CMR images of patients with acute myocarditis to assess left ventricular function and early gadolinium enhancement [52]. A total of 41 regions of the myocardium were found to have early gadolinium enhancement (EGE) irregularities. In the study, artificial intelligence algorithms applied to EGE derived from CMR proved useful for detecting acute myocarditis in patients. Thus, AI could automate the evaluation of gadolinium enhancement on cardiac MRI in the cardio-oncology population to detect early signs of subclinical myocarditis. For these patients, timely detection of acute myocarditis is crucial for administering cardioprotective therapies to improve survival.

Utilizing non-contrast chest CT images, AI can be used to develop a reliable cardiovascular disease risk profile for cancer patients undergoing cancer treatment planning or monitoring [21]. In a study using a deep learning algorithm, a predictive model was developed to assess cardiovascular risk based on a dataset of 30,286 low-dose CT scans procured from the National Lung Cancer Trial [53]. The model demonstrated an impressive ability to identify patients with elevated cardiovascular mortality (as indicated by an AUC of 0.768). This transformed the low dose CT scan, originally intended for lung cancer screening, into a valuable instrument for cardiovascular risk evaluation. Coronary calcium scoring is a known indicator of subclinical coronary artery disease. Artificial intelligence-based CAC features detectable on low-dose CT scans of lung cancer patients can potentially enhance CAC assessment and cardiovascular risk identification, allowing a comprehensive preventive approach [54]. The findings may be applicable to cardio-oncology patients with various types of cancers who receive non-gated CT chest scans for either treatment planning or monitoring purposes.

The use of artificial intelligence has additionally been employed to evaluate prognostic indicators in nuclear cardiology. Fluorodeoxyglucose F 18 (18F-FDG)-PET uptake scans are utilized to assess cardiovascular adverse effects of immune checkpoint inhibitors (ICI). By stimulating cytotoxic T cells, ICI may worsen atherosclerotic vascular disease and contribute to major adverse cardiovascular events [55]. AI has the potential to monitor temporal changes in the distribution of labeled 18F-FDG in cancer patients [4]. Preventive measures for prospective patients could be facilitated by relating these changes to chemotherapy and cardiovascular outcomes. In a study, ML applied to PET scans was superior to logistic regression employing the SCORE risk model based on ESC guidelines in identifying patients at high risk of myocardial ischemia and major adverse cardiac events (MACE) [56]. Cancer patients undergoing chest radiotherapy are at an elevated risk for developing MACE and cardiac ischemia [56]. Therefore, the integration of this combined technique may serve as a valuable tool for tracking ischemic heart disease in this population.

Despite the unprecedented strides achievable through AI simulations in automating imaging interpretation and integration into risk assessment models, the technology is not immune to algorithmic bias, which could disenfranchise minority groups. Racial disparities in diagnostic imaging predate AI applications. In the United States, racial and ethnic minority groups are more likely to receive care in lower quality hospitals offering substandard quality imaging technology [57,58]. Additionally, AI imaging studies and clinical trials have historically failed to report the demographic content of their datasets, leading to results and conclusions that may not be generalizable to minority populations (Table 2). The AI studies in cardiology that have reported their demographic information, however, mostly present very insignificant percentages of racial and ethnic minorities compared to Caucasian data (Table 2). To illustrate, an AI/ECG algorithm designed by Mayo Clinic researchers to identify patients with left ventricular systolic dysfunction was trained on imaging data that was 90 % Caucasian [43]. Nevertheless, in another study from the same research group, the authors found similar predictions across diverse racial and ethnic populations [59]. Researchers must be intentional about creating diverse datasets, as inadequate representation within the input data leads to algorithmic bias, which can potentially skew the validity and generalizability of AI models. Some groups are purposefully measuring and reporting on the demographic diversity in their cohort data, which will be an important step in the field (for example, see [60]).

Table 2

Presence of reporting distribution of racial and ethnic demographics of participants in machine learning studies for cardiac disease prediction. Adapted with permission from [12].

Study description	Percent caucasian	Percent racial/ethnic minority	Reference
Myocardial perfusion imaging data and ML used to predict cardiac events	No demographic information	No demographic information	[2]
Clinical imaging registry created for development of ML diagnostic and prognostic tools	No demographic information	No demographic information	[3]
Investigated incidence of CV events in clinical practice with ML risk assessment tool	No demographic information	No demographic information	[23]
ML model detected presence of residual tumor versus benign tissue in testicular cancer patients	No demographic information	No demographic information	[27]
ML-assisted prediction of late-onset cardiomyopathy in childhood cancer survivors	No demographic information	No demographic information	[33]
ML model utilized to identify patients with heart failure with preserved ejection fraction	No demographic information	No demographic information	[37]
ML algorithm used left ventricular GLS to detect subclinical ventricular dysfunction	No demographic information	No demographic information	[38]
Deep learning model identified various CV diseases from clinical imaging.	No demographic information	No demographic information	[39]
ML utilized to identify patterns in ECG-derived strain measures to predict declines in LVEF	No demographic information	No demographic information	[40]
ML-enabled model detected LVSD from dyspnea patients presenting to the emergency department	90.5 %	African American: 4.3 %, Hispanic: 2.5 %, Other: 3.5 %	[43]
Assessment of whether an ECG-based AI tool enabled the early diagnosis of low EF.	No demographic information	No demographic information	[44]
Prospective validation of deep learning ECG algorithm used to detect LVSD.	No demographic information	No demographic information	[46]
Assessment of utility of an AI/ECG model for heart failure prediction.	73 %	African American: 36 %	[47]
Deep learning model used to predict atrial fibrillation risk from 12-lead ECG.	No demographic information	No demographic information	[48]
Utilizing deep learning to predict CV disease risks from lung cancer screening.	No demographic information	No demographic information	[53]
ML algorithms utilized to identify ischemia and other major adverse CV events.	Conducted in the Netherlands	Conducted in the Netherlands	[56]
Deep learning algorithm designed to detect low LVEF using 12-lead ECG data.	96.2 %	Black/African American: 1 %, Asian 1 %, Hispanic/Latino: 0.6 %, American Indian: 0.4 %	[59]
ML algorithms utilized to predict cancer therapy-related cardiac dysfunction.	No demographic information	No demographic information	[107]

AI: artificial intelligence, CV: cardiovascular, ECG: electrocardiogram, EF: ejection fraction, GLS: global longitudinal strain, LVEF: left ventricular ejection fraction, LVSD: left ventricular systolic dysfunction, ML: machine learning.

4. Bias: impact of healthcare disparities on AI algorithms

In addition to human intelligence, computer simulations can imitate human bias, thoughts, and prejudice, potentially propagating and exacerbating existing healthcare disparities [61]. AI algorithms are built on raw data from a broad range of data sources, including electronic and administrative health records, databases, social media, and remote monitoring platforms. When biased data is utilized in the training and validation of these algorithms, it results in biased AI powered healthcare delivery tools. Biases against underrepresented groups may result if the data used is not representative of the entire population [61]. Biases that result from erroneous assumptions regarding minority and underrepresented patient populations may lead to the provision of suboptimal care. With the continuous expansion of AI techniques, it becomes increasingly crucial to remain vigilant against these biases to safeguard the health of all individuals regardless of their social and economic backgrounds. It then becomes imperative to devise strategies that leverage AI to promote overall well-being. In a recent study, Obermeyer et al. reported systemic bias with a commonly used, industry-level AI algorithm that helps to predict and risk stratify patients receiving primary care based on severity and complexity of their illness [62]. The author's findings suggest that there is a racial bias in the perception of illness severity, where African American patients who are accorded the same severity of health risk by the algorithm are more ill than their Caucasian counterparts. According to the authors, the presence of racial bias significantly decreases the identification of African American patients for additional care by over 50 %. This bias was noted when the algorithm draws on healthcare expenditures as a substitute for health requirements. This is attributable to the significant disparity in the allocation of funds for African American patients with the same level of need, leading to a misleading conclusion that African American patients are healthier than similarly sick Caucasian patients [62].

Deep learning algorithms developed on homogeneous populations may lack generalizability and could potentially reinforce and worsen healthcare disparities [59]. Underrepresented and vulnerable populations have largely been omitted from current healthcare datasets [63]. Thus, the insufficient representation of these groups in AI algorithms datasets can limit their predictive accuracy. When trained on the dominant populations, algorithms may be limited in their ability to identify patterns in patient groups not previously encountered. Algorithmic bias is the result of systematic errors in AI systems that give unfair advantages or disadvantages to certain individuals or groups [64]. Statistics and social bias can influence the results, interpretations, and recommendations generated by these systems. For example, a skin cancer diagnosis algorithm trained primarily on images of lesions on light-skinned people performed poorly when applied to images of lesions in African American patients [65]. African Americans already have a high melanoma mortality rate which could be exacerbated by inaccurate skin cancer diagnoses if this AI model is applied to this population [66]. Addressing these issues requires the creation of comprehensive datasets such as the Diverse Dermatology Images (DDI) to ensure that these algorithms are sufficiently generalizable [67]. Underrepresented and vulnerable populations have largely been omitted from current healthcare datasets [63]. Thus, the insufficient representation of these groups in AI algorithms datasets can limit their predictive accuracy. When trained on the dominant populations, algorithms may be limited in their ability to identify patterns in patient groups not previously encountered. Algorithmic bias is the result of systematic errors in AI systems that give unfair advantages or disadvantages to certain individuals or groups [64]. Statistics and social bias can influence the results, interpretations, and recommendations generated by these systems. For example, a skin cancer diagnosis algorithm trained primarily on images of lesions on light-skinned people performed poorly when applied to images of lesions in African American patients [65]. African Americans have a high melanoma mortality rate, which could be exacerbated by further inaccurate skin cancer diagnoses if this AI model is applied to this population [66].

It is important to note that African Americans are disproportionally affected by cardiovascular diseases [68]. Yet, African Americans are underrepresented in cardiovascular clinical trials, including trials funded by the National Institutes of Health (NIH) [69–71]. This is the case in cardiology in general, and also in cardio-oncology [8,72]. Studies have also found that African Americans are more likely to adopt a new therapy developed in the context of inclusive clinical trials [73]. Therefore, ensuring that the demographics of clinical trial participants are representative of the population that will ultimately utilize the therapy may contribute to the potential for implementation, safety, and efficacy of novel therapies. It is therefore also imperative to integrate diverse data into research and ensuring equitable representation in clinical trials [74].

Despite inclusivity initiatives such as the NIH Revitalization Act of 1993, minority representation in heart failure trials continues to remain minimal [71]. This underrepresentation can limit the generalizability of trial results and thus can hinder the development of treatments effective across populations. A compelling example is the landmark African American Heart Failure Trial, which demonstrated a reduction in mortality using isosorbide dinitrate and hydralazine specifically in the African American population [75]. This example highlights the importance of including diverse populations in clinical trials, as medications may have different efficacy and safety profiles across populations depending on genetic, environmental, and socioeconomic factors. Without adequate minority representation, the results of heart failure trials can lead to overgeneralization, which may result in less effective or even harmful treatment recommendations for underrepresented groups. Despite this being demonstrated, challenges remain in optimizing minority representation in clinical trials. For example, in a recent study such as the PARADIGM trial—which evaluated the angiotensin receptor-neprilysin inhibitor compared to enalapril for improving cardiovascular death and heart failure hospitalization—5.1 % African American patients out of 8399 participants were enrolled [70]. This underrepresentation in pivotal cardiovascular trials complicates the assurance that heart failure treatments are both safe and effective for African American patients. Solutions suggested include diversifying the clinical trial workforce, enhancing community engagement, and rebuilding trust within the African American community [76]. The underrepresentation of African American individuals in leadership positions in healthcare may exacerbate mistrust toward the medical community and hinder their inclusion in larger clinical trials [77].

It is therefore also crucial to build a healthcare workforce that is both diverse and culturally competent [74]. Leveraging digital tools can also enhance the diversity of clinical trials by making participation more accessible through electronic consenting when needed [78]. This of course depends on ensuring equity in broadband internet access as well. These steps are crucial for advancing equity in cardiovascular care.

When utilizing artificial intelligence algorithms in healthcare, it is imperative to undertake subgroup analysis and AI validation in diverse demographics to mitigate the risk of latent partiality in the algorithms [59]. A Mayo Clinic study modeled an AI algorithm trained on 45,000 non-Hispanic whites only and then tested it on different cohorts of an equal number of multiethnic patients [59]. The AI algorithm was similarly predictive across all ethnicities, as shown by a similar AUROC (area under the receiver operator characteristics) of 0.9 for all cohorts (including Hispanic/Latino, Black/African American, American Indian/Native Alaskan, and Asian). While the present algorithm exhibited race-neutrality in its efficacy, alternative algorithms may lack this attribute.

Numerous studies have reported higher rates of cancer therapy induced cardiotoxicity among African Americans, however, relatively few studies have studied the racial and ethnic outcomes of certain chemotherapeutic agents, including anthracyclines and trastuzumab [72]. The review of research examining the use of beta blockers, angiotensin-converting enzyme (ACE) inhibitors, statins, dexrazoxane, and lifestyle alterations to prevent cardiotoxicity revealed underrepresentation of racial and ethnic minorities in published research, with the majority of studies failing to include any demographic information pertaining to race or ethnicity [72]. Similarly, gender disparities can be exacerbated by unbalanced AI algorithms. As cardiovascular disease manifests itself differently in men and women, an algorithm trained primarily on data samples from males may not be as accurate when diagnosing women [79]. It is of utmost importance that artificial intelligence algorithms designed for widespread implementation prioritize validation procedures that account for the diversity inherent in the target demographic.

Certain algorithms utilized in healthcare lack sufficient regulation in the United States. Although certain medical devices and tools, including AI, are subject to regulation, there is a lack of regulation for algorithmic decision-making tools utilized in clinical, administrative, and healthcare settings. These tools, which can predict risk of mortality, readmission risk, and in-home care needs, are not mandated to undergo review or regulation by the FDA or any other regulatory body. Without proper oversight, the use of biased algorithms can become widespread within healthcare institutions and state public health systems, resulting in heightened discrimination against marginalized communities. At times, the lack of regulation can result in financial waste and tragic loss of life. Although the FDA recommends that device manufacturers conduct tests for racial and ethnic biases prior to marketing their devices to the public, this step is not mandatory. Transparency during the development of a device is crucial, possibly even more so than assessments conducted after its completion. According to a recent study, it has been discovered that a significant number of AI tools authorized or cleared by the FDA lack information regarding the diversity of the data used for training [80].

5. Digital health tools: telemedicine, wearables, remote patient monitoring

Cardiovascular adverse effects often necessitate referral to cardio-oncology clinics [81]. However, most cardio-oncology programs are domicile in large academic referral centers [17]. Yet, the majority of cancer patients receive treatment at local healthcare facilities without these programs [17]. Therefore, expanding access to specialized cardio-oncology care to patients in these settings will improve access and survival. The National Cardio-Oncology Survey conducted by the American College of Cardiology (ACC) revealed challenges to establishing cardio-oncology programs, including inadequate infrastructure, funding, specialized training programs, and guidelines for cardio-oncology practice [82]. Cardio-oncology programs can enhance their growth and success by leveraging the resources provided by their professional societies to obtain guidance, support, and provide opportunities for global collaborations.

For patients with limited access to healthcare, for example, those in rural communities, AI-powered remote monitoring systems can be combined with telemedicine to promote access. The pandemic spurred an unprecedented expansion of telemedicine. However, health equity experts have expressed concerns regarding how to monitor telemedicine usage to ensure that it does not exacerbate current poor access to healthcare and exacerbate disparities. In this regard, a National Office of Health Policy study revealed that the proportion of telehealth video visits was higher among individuals with a bachelor's degree or higher, a yearly income of $100,000 or more, private insurance, and Caucasian ethnicity [83]. Among Caucasians, the proportion of video telehealth visits was higher compared to the number of audio-only telehealth visits (61.9 % versus 38.1 %, respectively). In the case of African Americans, the proportion of telehealth audio visits was higher than the percentage of telehealth video visits (53.6 % vs 46.4 %). This finding could be partly explained by a PEW survey that showed that among all US adult respondents, Caucasians were more likely to have home broadband internet [84]. The possession of smartphones was surveyed among those without residential internet access, and Caucasians outperformed other ethnicities, with around 10 % to 20 % of African Americans owning smartphones. Therefore, broadband internet has been described as an emerging social determinant of health [85]. These factors should be considered when examining racial and ethnic disparities in cardio-oncology. For example, studies on successful and reproducible approaches for operating cardio-oncology telehealth clinics, including virtual-hybrid, or triage clinics, have been published in the field of cardio-oncology [86–88]. However, these studies did not specifically indicate the demographic distribution of their populations. Future directions should include exploring this further. Additionally, ensuring data security is also essential. While digital technologies and AI have the potential to reduce healthcare disparities, overcoming the historical and structural inequities embedded in clinical practice requires intentional efforts of security including the inclusion of appropriate safeguards to prevent exploitation [89].

During the coronavirus disease of 2019 pandemic, it became imperative to adapt to a virtual avenue for providing care to cardio-oncology patients. This was in efforts to mitigate the downstream effects of delayed care in terms of financial cost, health consequences of delayed testing and treatment especially in cancer patients who constantly under time constraints. In a pilot program, a virtual hybrid cardio-oncology clinic was developed and may serve as a template for centers seeking to develop new virtual and/or in person clinics. The hybrid care spectrum involved clinic visits completed in person or virtually by video or telephone calls [86]. An additional study by Sadler et al. presented a cost-effective and practical directive to establishing and sustaining a cardio-oncology program [87]. To achieve this, they propose four fundamental elements including a clinical program consisting of existing staff and resources; an education program that will enlighten the staff and team members regarding cardiotoxicity and care of the cardio-oncology patient; engagement with professional societies and industry leaders; establishing a research program to enable data collection and collaboration with other institutions. Triage clinic workflow has been proposed [86,87]. Initial triage may be performed by the cardio-oncology clinic personnel or the referring physician, contingent on the institution's workflow. Patients with a high cardiac risk may be scheduled for virtual consultations with cardio-oncologists following this triage process. Patients at low or uncertain risks may have their virtual consultations arranged in advance by a cardio-oncology nurse or advanced practice practitioner navigator. The navigator possesses the capability to acquire additional clinical data and pertinent patient records to adequately evaluate the cardiac risk prior to consulting a cardio-oncologist in person or virtually [88].

AI has been instrumental in the development of digital health platforms and wearables for remote patient monitoring, such as blood pressure and heart rate monitors, pulse oximeters, and glucose monitors (Fig. 1). AI may also improve the identification and management of at-risk patients through advanced predictive analytics [90]. By integrating AI with digital health tools—such as wearable devices that monitor cardiovascular health and EHRs—healthcare providers could enable more precise and timely interventions for those at risk of cardiotoxicity. For example, AI-driven algorithms could analyze data from continuous glucose monitors or blood pressure cuffs to predict adverse cardiovascular events in real time, allowing for early intervention. However, diverse, representative data must be used to train AI systems to ensure that the benefits of these advanced technologies are equitably distributed across all populations.

An ongoing initiative in telemedicine is the development and utilization of remote patient monitoring systems that utilize cell phone towers independent of internet systems [7]. This will be a potential research avenue for examining its impact on improving access and health outcomes. In most research studies that reported racial and ethnic data in their data analysis, African Americans comprised a minority of the study population but had worse cardiotoxicity and poor outcomes [91]. The signals underlying these outcomes tend toward social determinants of health. The overall factors contributing to racial and ethnic disparities in cardio-oncology include underrepresentation in clinical trials, social determinants of health, rates of cancer mortality, rates and inadequate management of hypertension and heart failure, large cardiac risk factor burdens, precision medicine and innovation, access to healthcare screening and providers, and implicit and explicit biases [8]. Proposed solutions to mitigate these disparities include the development, training, validation, and dissemination of biotechnological and innovation tools for minority populations [8]. Additionally, the encouragement of collaboration among cardiologists, oncologists, and primary care providers, can aid in addressing the unique challenges faced by minority populations [72].

Thoughtful and meaningful integration of social and cultural factors into patient care is also key [72]. Further, integrating community preferences can also aid in bridging the digital divide, especially from socioeconomically disadvantaged and underrepresented groups. Digital interventions can become more relevant, acceptable, and effective when integrated with community-informed approaches [92]. Partnerships with community leaders and advocacy groups can build trust and ensure digital inclusion. Collaboration among federal agencies, industry, and academia can also play a crucial role in influencing policies and funding to bridge the digital divide, expand access, and support equitable clinical research.

However, the digital divide remains a significant challenge, as unequal access to technology can hinder patient education, limit participation in telemedicine, and reduce awareness of available healthcare services. Bridging this gap through initiatives that expand internet access, provide digital literacy training, and supply devices can significantly improve healthcare outcomes for underserved populations. While telehealth offers numerous benefits, such as greater access to specialized care and convenience, these advantages can only be fully realized by addressing the digital divide [78]. In considering these disparities, it is essential to recognize race as a social construct, shaped by differential environmental exposures and risks, rather than a biological factor [72,93]. This perspective emphasizes the importance of addressing the systemic issues that underlie health inequities, leading to more effective strategies in tackling disparities in cardio-oncology [94].

6. Application of machine learning in clinical practice

Machine learning is a crucial aspect of artificial intelligence, with two primary divisions: supervised and unsupervised learning [26]. Supervised learning involves creating mathematical models that utilize known samples with certain features as training sets. These models are then used to map new unknown samples based on the established patterns. Supervised learning methods typically consist of logistic regression, decision tree, support vector machine (SVM), naïve bayes, random forest (RF), and artificial neural network models. Examples of application of supervised ML is in disease diagnosis and risk prediction models. Unsupervised learning involves problem solving by recognizing patterns based on training samples with unknown categories. The primary methods of unsupervised learning models include K-means and hierarchical clustering methods. A specific example of unsupervised ML application would be to identify novel subcategories of diseases and further classify them into more specific and distinct subcategories [30]. In cardiology, applying advanced technology such as ML to imaging assessment, and ECGs, has greatly enhanced the diagnosis of cardiovascular disease. ML algorithms can construct prediction models that assist clinicians in making more informed clinical decisions [30].

EHRs utilized in the routine patient care offer a distinct repository for combined clinical and imaging data for cardio-oncology patients. Utilizing EHR data obtained during clinical care would be a more practical approach for creating pragmatic registries, that would allow easier scalability, as opposed to manually abstracting information from charts. Machine learning can be used to analyze unstructured EHR data to identify patients who require specialized care (Fig. 1). This strategy reduces the time and effort needed to discover gaps in care and improves patient access. This requires a sufficient infrastructure and the ability to securely retrieve medical records, which could enable personalized patient care. A supervised Komenti text-mining framework (a reasoner-enabled semantic query and information extraction framework) was utilized on specified clinical letters to identify patients with hypertrophic cardiomyopathy who were not receiving specialized care [95]. It also determined their atrial fibrillation and heart failure status, as well as their use of anticoagulants. The approach was assessed by conducting expert manual validation and comparing the derived cohort with coded EHR data. After careful analysis, a total of 1753 confirmed cases of hypertrophic cardiomyopathy were identified. Among these cases, 333 patients had a positive family history, 357 had atrial fibrillation, and 205 had heart failure. Through manual validation, an accuracy rate of 86.3 % (95 % CI: 82.3 %–90.3 %) was identified with a sensitivity of 86.5 % against the EHR data. There was a lack of expert care for the 214 patients found using the text-mining method [95]. The prescription for anticoagulant had an accuracy rate of 93.6 % (95 % CI: 88.6 %–98.6 %). After reviewing clinical records, care gap in anticoagulation management was discovered in 39 patients with atrial fibrillation. Those were then referred for further treatment to prevent stroke and thromboembolism [95]. This framework could be validated on cardio-oncology patients to identify care gaps and need for specialty referral. Specialized condition registries can be quickly created using reproducible platforms within a feasible time frame, which can subsequently be utilized for research purposes [96]. A recent study investigated the feasibility of creating a cardio-oncology registry using existing EHR data [96,97]. The results of the study supported the utility of care registry in identifying care gaps. Mandating unified medical language systems/terminologies like SNOMED (Systematized Nomenclature of Medicine Clinical Terms), LOINC (Logical Observation Identifiers, Names, and Codes) and RxNorm in the development of EHR systems can foster multisite research collaboration [96,98]. Thus, successful conduct of multicenter research can be enhanced by implementing a standardized data model. Adopting a practice of creating SQL code once to convert the data models of various large EHR suppliers into a single data model, and subsequently sharing these adapted SQL code scripts with the customers of each vendor, will considerably simplify multi-institutional, multi-EHR clinical research in the future. Future applications of ML and other artificial intelligence to analyze cardio-oncology clinical and imaging data contained in patient EHR will progressively provide valuable insight.

Traditionally, referral of cancer patients and survivors for cardiovascular care occurs when the treating oncologist detects symptoms of cardiotoxicity. This referral system is subjective, and care for at-risk individuals could be delayed. Although inroads have been established in cardio-oncology care, there is still an underdeveloped work-flow infrastructure to foster and support collaborative partnerships between cardiology and oncology practices [99]. Al-Droubi et al. applied ML algorithms to identify oncology patients at risk of developing cardiovascular disease for referral to cardio-oncology specialist and to generating risk scores to support quality and timely intervention [25]. The clinical risk forecasting model was created by assessing the patient's history available in the electronic health record, including pre-existing diseases and conditions that emerged when exposed to cancer regimens. The model revealed that majority of at-risk cancer patients were not being appropriately referred to a cardiologist. The authors propose that this ML model can automate this process, unburden care providers, and reliably review available patient data to recommend those requiring timely cardio-oncology care [25]. There are a few limitations to note when considering the present investigation. These include the use of a retrospective study design and a relatively small cohort for validation, which specifically focused on only four types of cancer. Additionally, more research is needed to determine how well the model can be applied in real-world clinical settings. Despite the promise ML models hold in healthcare, they have several limitations. One of these is the lack of consideration for humanistic ethics when applied to decision process or predicting risks. Another limitation is the “black-box” effect, where these models operate through obscure internal mechanisms, making their calculation processes incomprehensible to humans and rendering them unexplainable and uncertain [30].

The performance of ML and AI algorithms can also be limited by lack of data, data sorting and storage formats. The efficacy of AI is contingent upon the availability of sufficient data for analysis, training, and performance. In the absence of adequate data, the feasibility of a reliable algorithm becomes unattainable. In recent years, governments, funders, and institutions have collaborated to encourage the dissemination of publicly available data. The availability of open datasets for algorithms training and development has expanded because of data repositories [63]. However, AI algorithm training datasets available for public use lack diversity, disaggregation, and interoperability constraining data utility and applicability. The integration and utilization of open datasets in complex systems is hindered by inconsistencies, incoherences, formatting discrepancies, and inadequate disaggregation of data [63]. Further, data may be stored in a way that makes it difficult to retrieve. For example, clinical data could be embedded in siloed imaging machines, electronic medical records or paper charts that are not connected to the whole data, making it difficult to distill and integrate information [63,100]. An additional point of consideration is data security. Adequate safeguards are warranted when handling sensitive information to prevent exploitation [89].

7. Multidisciplinary teams in preventing and mitigating bias in cardio-oncology

Despite previously mentioned challenges, there are several opportunities to integrate and implement AI across health systems, interdisciplinary teams, and multidisciplinary training. The role of collaborative teams is invaluable. These teams can include medical students, clinicians, data experts, and individuals at different stages of training. Considering the complexities involved in building a more inclusive AI simulation tool, multi-institutional collaborative teams with diverse backgrounds can offer insightful and equitable perspectives [101]. Two of such teams are Patient Similarity Algorithms in the Prevention of Cardiovascular Toxicity (PACT) and the Cardio-oncology Artificial Intelligence Informatics and Precision Equity (CAIPE) research teams. These teams are comprised of investigators from various U.S. and Canadian institutions with diverse areas of expertise including cardio-oncologists, experts in cardiotoxicity research and bioinformatics, digital health and innovation, surgical oncology, data science and precision medicine, cardiac imaging, clinical decision support, pharmacology and toxicology, computer science engineering and AI, biostatistics, electronic health records informatics, legal counsel, patient advocates, research development, and biophysics. Their collaborative project involved the creation of a large database consisting of >4000 patients pooled from the electronic health records of >1.2 million cancer survivors with data spanning >20 years, stored in a clinical data warehouse at Froedtert and the Medical College of Wisconsin (F&MCW). This cohort consists of multi-ethnic adults of equal male to female ratio, at least 18 years old with echocardiographic ejection fraction assessment within 3 years prior to cancer diagnosis. The objective is to evaluate the feasibility and efficacy of implementing an AI-driven clinical decision support tool in the context of collaborative decision-making between a cancer survivor patient and a cardiologist, with focus on preventing cardiovascular disease [102].

Comprehensive, multidisciplinary approaches are essential to addressing healthcare disparities. Racial and ethnic disparities in cardio-oncology are deeply rooted in historical and structural practices, which contribute to a higher prevalence of cardiovascular disease risk factors, limited access to specialized care, socioeconomic barriers, and under-representation in these communities. For example, African American individuals face worse cardiovascular health outcomes, including higher rates of fatal cardiovascular disease compared to non-Hispanic whites, primarily due to systemic inequities [103]. Similarly, Hispanic populations experience elevated cardiometabolic risks, such as higher rates of obesity and diabetes, increasing their vulnerability to cardiotoxicity from cancer treatments [104]. It is also important to understand that systemic biases may lead to diagnosis of cancers in the African American population at more advanced stages which may require more cardiotoxic treatment and thus predispose this population to more cardiotoxic side effects [105]. Consequently, more intentional and robust efforts to mitigate biases and improve early access, screening, and awareness for at-risk populations are needed.

Expanding community engagement through mobile clinics and partnerships, along with improving access to care via telemedicine and specialized clinics in underserved areas, are key steps toward better outcomes in cardio-oncology [106]. Mobile clinics, for example, offer a flexible and effective way to reach populations with limited access to healthcare facilities. Mobile clinics additionally collect valuable data on patient demographics, health behaviors, and disease prevalence. Having the combination of clinical and sociodemographic data helps tailor clinical interventions to specific community needs. Mobile clinics are commonly deployed in underserved or marginalized communities including rural areas, low-income urban neighborhoods, and regions where access to healthcare facilities is limited due to geographic, financial, or social barriers. One of the key benefits of mobile clinics is their ability to collect valuable data on patient demographics, health behaviors, and disease prevalence. Additionally, they help build trust within communities by providing consistent localized care, overcoming barriers that prevent marginalized groups from accessing cardio-oncology services.

8. Conclusion

Cardio-oncology focuses on preventing and managing cardiovascular complications associated with cancer treatments. Early diagnosis and screening remain challenging because of limited access to care and inaccurate prediction of cardiotoxicity risk. Creating effective and accurately predictive AI models for early forecasting and identification of cardiovascular diseases is crucial in this population. To maximize the use of AI in the treatment of cardiovascular risks while promoting and achieving health equity, practices-changing strategies must be included, as well as metrics collected, data analyzed, interpreted by researchers, and strategies for risk prevention implemented in clinical practice based on these findings. Further, clinicians should adopt a mindset that incorporates equity into clinical practice and ensures that research studies are inclusive to combat existing disparities. As innovative health tools are developed, careful consideration must be given to the requirements of a diverse, multiethnic population.

CRediT authorship contribution statement

Gift Echefu: Writing – review & editing, Writing – original draft. **Rushabh Shah:** Writing – review & editing. **Zanele Sanchez:** Writing – review & editing. **John Rickards:** Writing – review & editing. **Sherry-Ann Brown:** Writing – review & editing, Conceptualization.

Consent for publication

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Declaration of competing interest

Dr. Sherry-Ann Brown is the Founder of the Heart Innovation and Equity Research (HIER) Group. All other authors have no competing interests.

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Data availability

Data can be provided upon request.

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