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Artificial Intelligence in Congenital Heart Disease: A Roadmap

REVIEW

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ABSTRACT

Congenital heart disease (CHD) is a lifelong condition that requires ongoing monitoring due to its heterogeneous anatomy, physiology, and clinical course. Despite major advances in diagnosis and treatment, challenges remain in early detection, risk stratification, and long-term management. Artificial intelligence (AI) has the potential to enhance CHD care by extracting actionable insights from complex clinical data. This review examines current and emerging applications of AI in three key domains: cardiovascular imaging, wearable technologies, and clinical registries. We highlight opportunities to improve diagnosis, monitoring, and outcome prediction, while discussing important challenges related to data quality, validation, interpretability, and clinical implementation. Together, these areas illustrate both the promise and the barriers to integrating AI into CHD care.

KEYWORDS:
congenital heart disease (CHD); artificial intelligence (AI); cardiovascular imaging; wearable health technologies

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INTRODUCTION

Congenital heart disease (CHD) is comprised of a heterogeneous group of structural malformations that vary widely in anatomy, physiology, severity, and clinical course (Figure 1). CHD affects approximately 9 per 1,000 live births worldwide, but its burden extends well beyond just prevalence.[1] As of 2021, more than 4.18 million children younger than 5 years were living with CHD, and mortality remained concentrated in low- and low-middle-sociodemographic index regions.[2] This disparity reflects major differences in timely diagnosis, access to intervention, and longitudinal care.[3] In the United States (US), nearly 40,000 infants are born with CHD each year, and about one in four has a critical defect that usually requires surgery or catheter-based intervention during the first year of life.[4] Despite existing screening approaches, late detection of CHD remains common in the US, affecting 16.4% of infants in a recent multisite study.[5] Rates may be substantially higher in resource-limited settings.[3] Delayed detection is associated with a worse preoperative condition, more hospital admissions, longer hospitalization, and higher inpatient costs. CHD also carries a substantial financial burden.[6,7] In 2019, US hospital costs for individuals with heart defects exceeded $9.8 billion.[8] Families may face additional out-of-pocket expenses, substantial caregiving demands, and loss of employment or working hours.[9]

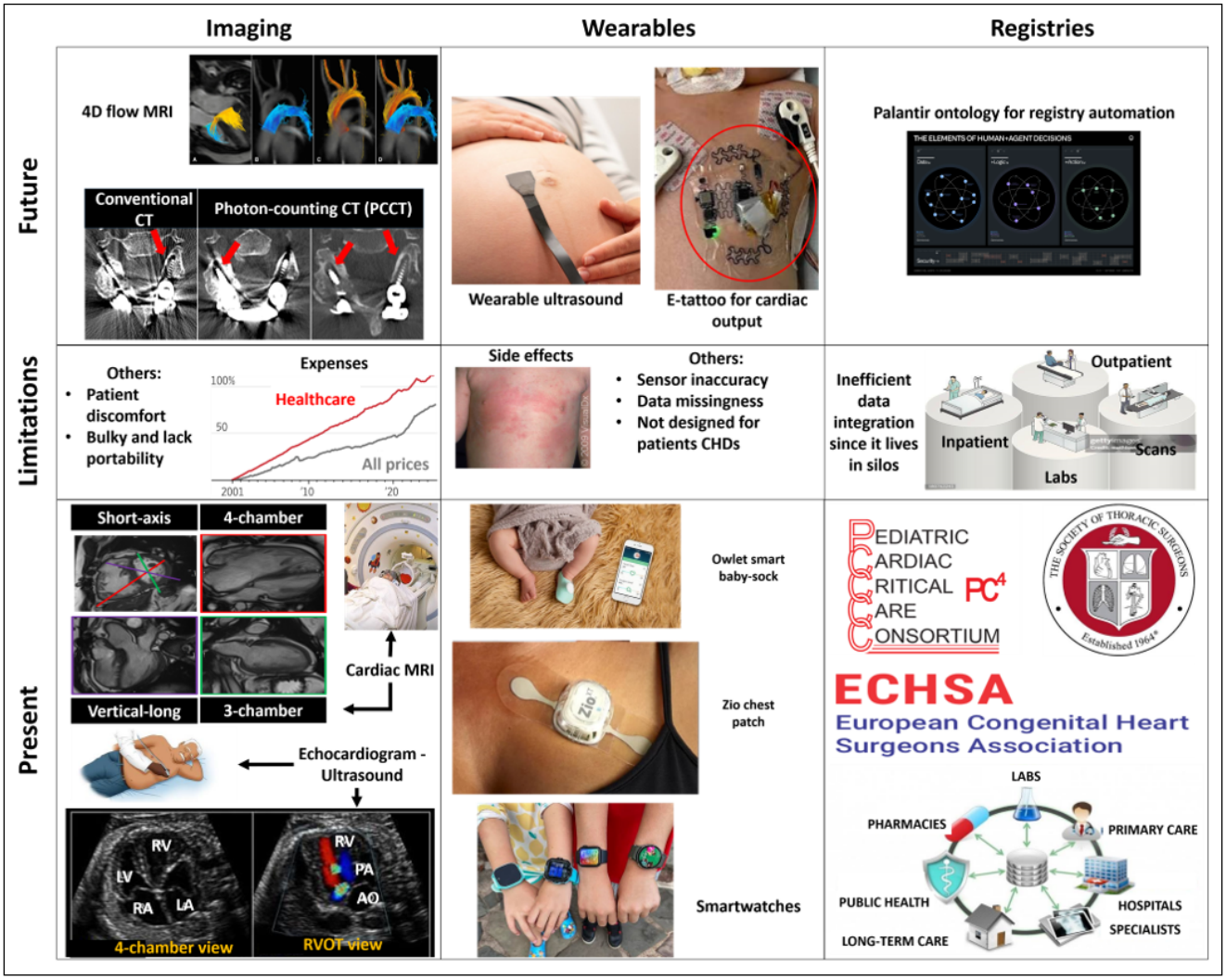


Figure 1 Imaging, wearables, and registries as foundational data sources for translational artificial intelligence in congenital heart disease (CHD). The heterogeneous nature of CHD creates opportunities for AI to improve care in a variety of ways. (Left) Imaging in CHD could be improved with novel techniques like 4D flow MRI and photon-counting CT but already is being used in CMR and echocardiography. (Middle) Wearable biosensors allow collection of continuous physiologic data in a variety of settings, but may expand to further physiologic values (eg, ultrasound or seismocardiography) in the future. Clinical and research registries (right) are designed to collect large-scale data but often capture data only from fragmented portions of the patient journey. In the future, automation of registry data entry and data linkages may improve the impact of these data. CMR: cardiac magnetic resonance imaging; RV: right ventricle; LV: left ventricle; RA: right atrium; LA: left atrium: PA: pulmonary artery; AO: aorta; AI: artificial intelligence

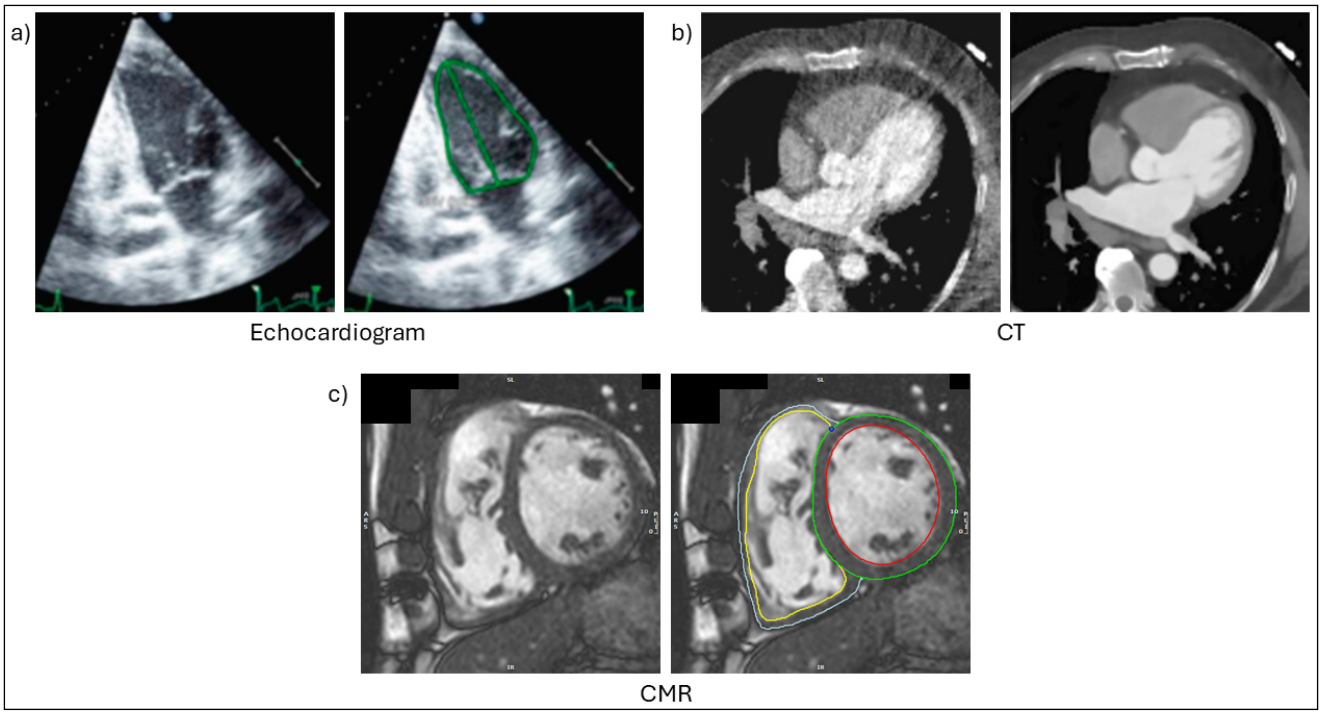


Figure 2 (A) Automated contouring of a 2-chamber view echocardiogram, with the green outline showing segmentation of the endocardial border for function calculations. **(B)** Reduction of noise in low-intensity CT scan, which would allow improved imaging quality with decreased radiation exposure. **(C)** Manual contour of short axis stack view CMR. Manual contouring is a time-consuming process, so effective automation can improve clinical workflows. CT: computed tomography: CMR: cardiac magnetic resonance

Advances in diagnosis, surgery, catheter-based treatment, and intensive care have transformed CHD into a lifelong condition. In contemporary high-resource settings, more than 97% of children with CHD may reach adulthood.[10] Survival, however, is not equivalent to cure. Many patients continue to face residual hemodynamic abnormalities and arrhythmias. Functional limitations, neurodevelopmental difficulties, and later reinterventions further shape their long-term outcomes and quality of life. Therefore, patients with CHD require lifelong care as well as lifelong monitoring because clinical trajectories vary even among patients with the same diagnosis.[11] Relevant information is distributed across a broad range of data types, including imaging and physiologic monitoring. Procedural records and longitudinal clinical documentation provide additional context but are often stored separately. CHD care therefore remains highly specialized and dependent on expert interpretation.

Artificial intelligence (AI) may help close this gap by extracting reproducible information from complex data and supporting individualized assessment at scale.[12] In this review, we focus on three domains that are central to this opportunity. Imaging provides detailed assessment of anatomy and function. Wearables extend physiologic observation beyond episodic clinical encounters. Registries provide the scale, standardization, and longitudinal structure required for evidence generation and model validation. Together, these domains illustrate both the promise of AI in CHD and the practical barriers that must be addressed before widespread clinical translation.

FOUNDATIONS FOR TRANSLATIONAL AI IN CHD

To realize this potential, AI in CHD must be grounded in data streams that reflect how congenital heart disease is diagnosed, monitored, and studied across the lifespan. The following sections examine how imaging, wearables, and registries are shaping the development, validation, and clinical translation of AI across the CHD care pathway (Figure 1).

IMAGING: AUTOMATING ANATOMICAL AND FUNCTIONAL ASSESSMENT

Three of the most common imaging modalities used in CHD are echocardiography, cardiac computed tomography (CT), and cardiac magnetic resonance imaging (CMR).[13-15] Echocardiography, also known as cardiac ultrasound, is the most widely used and accessible modality. It is relatively inexpensive, portable, radiation-free, and provides real-time image assessment of cardiac anatomy and blood flow. The downside is that image quality is highly dependent on patient characteristics and operator experience.[13,16] CT scans use x-rays to provide a 3-dimensional scan of the

heart. While they provide more precise images compared to echocardiograms, they have a risk of radiation exposure and lack portability.[14] CMR is noninvasive, avoids radiation, and provides comprehensive assessment of cardiac function, flow, and tissue characterization.[15,17] However, CMR scanners have limited availability, high costs, and long scan times with substantial expert-level post processing times.

CHD-specific AI applications are most established in echocardiography disease detection and automated analysis (Figure 2). AI has been used to identify CHD from both fetal and postnatal echocardiographic images.[18,19] Automated approaches are also being developed to perform structural and functional measurements that traditionally require manual interpretation, including measures such as longitudinal strain.[20,21] These applications could significantly reduce manual workload and improve standardization. However, echocardiographic image quality and imaging views vary substantially across CHD patients and operators; this is further complicated by varying anatomy, which limits AI model generalizability.[22]

Preliminary evidence from other non-CHD specific cardiovascular imaging literature shows promise. AI-guided image acquisition has enabled users with limited echocardiographic experience to obtain diagnostically useful studies, suggesting a potential strategy for reducing operator dependence in CHD imaging. Similarly, AI-assisted CT positioning and image reconstruction have been used to reduce radiation exposure and improve image quality in non-CHD cardiovascular imaging.[23,24] These approaches are attractive for CHD, particularly for pediatric populations, which requires balancing the conflicting goals of repeated imaging for higher image quality while minimizing patient radiation exposure. However, congenital anatomy, smaller patient size, prior surgical reconstruction, and altered hemodynamics mean that these approaches require dedicated validation studies before they can be adopted to CHD populations.

CMR provides some of the strongest CHD-specific evidence for AI-based automation. Conventional CMR post-processing requires manual tracing of cardiac structures across multiple image slices, which can be time-consuming and subject to interobserver variability.[17,25] Automated segmentation models have therefore been developed to reduce contouring time and standardize ventricular measurements.[26] This task is particularly challenging in CHD because of marked anatomical heterogeneity, and adult-trained models can underperform when applied

STUDY	POPULATION AND SETTING	AI-ENABLED CLINICAL USE	MAIN FINDING	TRANSLATIONAL STATUS	KEY REMAINING GAP
Narang et al., 2021[22]	Adults undergoing echocardiography, prospective two-center study, n = 240; not CHD-specific	Real-time guidance for novice echocardiographic acquisition	Novice nurses obtained images suitable for assessing LV size and function in 98.8% of studies and RV size in 92.5%	Prospective workflow evaluation	Limited cardiac assessment and no CHD-specific validation
Knackstedt et al., 2015[21]	Adult echocardiography; not CHD-specific	Automated measurement of ejection fraction and longitudinal strain	Demonstrated the feasibility of fully automated functional assessment with reduced dependence on manual tracking	Clinical validation	Performance in congenital anatomy and systemic right ventricles remains uncertain
Sandfort et al., 2024[24]	Retrospective cardiac CT cohort, n = 566; not CHD-specific	Deep-learning denoising of reduced-quality multiphase CT	Improved image quality and supported automated functional analysis of noisier CT data	Technical validation	No direct validation in pediatric or congenital CT
Tandon et al., 2021[27]	Repaired tetralogy of Fallot, single-center CMR cohort; 57 training and 30 testing cases	CHD-specific retraining of an existing ventricular-contouring CNN	Adding a small rTOF dataset improved RV contouring and reduced RV end-diastolic volume error from 11.4% to 8.1%	Internal CHD validation with early clinical translation	Small, single-lesion cohort with no multicenter testing
Yao et al., 2024[28]	Single-ventricle CMR registry across multiple institutions; evaluated on 475 unseen examinations	Automated ventricular segmentation and volume assessment	Segmentation was satisfactory without correction in 68% of unseen examinations. A further 26% required only minor adjustment	Multicenter registry validation	Approximately one-third of examinations still required human correction
Gritti et al., 2024[69]	Pediatric cardiac multimodal imaging evaluation	Assessment of general-purpose AI for cardiac image interpretation	General AI tools showed insufficient precision for dependable pediatric cardiac interpretation	Technical benchmark	Generic models remain unsuitable for complex CHD imaging without task-specific training

Table 1 Imaging-related studies that made use of artificial intelligence for analysis. The table outlines the study, the application of AI, findings, and the key remaining gap for clinical utility. CHD: congenital heart disease; LV: left ventricular; CT: computed tomography; CMR: cardiac magnetic resonance; rTOF: repair tetralogy of Fallot; RV: right ventricular; AI: artificial intelligence; CNN: convolutional neural network

to congenital cases, especially in pediatric populations.[27] As larger CHD-specific datasets become available, segmentation performance will continue to improve.[28] AI is also being explored for downstream analysis of cardiac structure and prognosis, while broader CMR work on accelerated acquisition may ultimately help shorten congenital CMR examinations.[29]

Overall, imaging AI in CHD spans different levels of maturity. Direct CHD evidence is strongest for disease detection and CMR segmentation, whereas much of the evidence for AI-guided acquisition, CT dose reduction, and scan acceleration remains extrapolated from broader cardiovascular imaging. These cross-cutting applications are highly relevant to CHD, but their clinical translation will require CHD-specific external validation across heterogeneous anatomy, age groups, imaging platforms, and centers followed by prospective assessment of whether they improve workflow or clinical decision-making (Table 1).

WEARABLES: EXTENDING PHYSIOLOGIC MONITORING BEYOND THE CLINIC

Despite the requirement of lifelong surveillance in congenital heart disease, clinical follow-up usually remains episodic. Wearable sensors offer the possibility to extend physiologic monitoring beyond scheduled clinical encounters and into patients' daily lives. Smartwatches, ambulatory electrocardiography (ECG) patches, and multiparametric sensors can capture ECG, photoplethysmography, accelerometry, phonocardiography, peripheral oxygen saturation, and respiratory rate proxies over longer periods while remaining unobtrusive. These data may support screening, diagnosis, and longitudinal surveillance, while AI can enable automated interpretation and detection of clinically relevant changes (Figure 3). The potential importance of this approach in CHD has also been highlighted by the American Heart Association, which identified continual noninvasive monitoring outside the hospital as an important opportunity for wearable biosensors in pediatric and congenital heart disease.[30]

CHD-specific wearable literature constitutes a very small percentage of the broader cardiovascular populations, yet the available evidence spans several clinically meaningful applications. In a prospective study of 215 children with and without CHD, Apple Watch iECG recordings were reliably interpretable in 94.9% of cases and showed excellent agreement with standard lead I ECG, supporting its potential for rhythm assessment outside conventional ECG testing.[31] Multimodal sensing combining ECG and seismocardiography has demonstrated feasibility for estimating stroke volume in a heterogenous cohort of children with CHD when compared with gold-standard CMR (R^2 of 0.76).[32] More recently, a soft wearable platform combining a chest biopatch with pulse oximetry was developed specifically for home monitoring of infants with single-ventricle heart disease, enabling continuous physiologic data transmission and automated alerts to caregivers.[33] Together, these studies are important because they move wearables beyond simple activity tracking to measurements directly related to CHD physiology, which also forms an integral part of their clinical care. They also establish a plausible translational progression with future studies focusing on taking evidence derived in controlled settings to outpatient monitoring and ultimately longitudinal monitoring across childhood and adulthood.

Broader pediatric and adult wearable studies provide supporting evidence for sensing applications relevant to CHD. The Zio ECG patch demonstrated substantial diagnostic yield in a national pediatric registry (n = 3,209), with 44% of first-detected arrhythmias and more than 50% of symptom-triggered events occurring beyond 48 hours of monitoring—highlighting the value of extended wear over conventional 24-hour Holter recording.[34] This is further supported by adult data showing greater diagnostic yield over total wear time with the Zio Patch compared with Holter monitoring.[35] Beyond ECG patches, wearable phonocardiography enables digital analysis of heart sounds and murmurs, with Chorba et al. demonstrating that AI-based murmur detection performs comparably to cardiologists.[36] These studies demonstrate the feasibility of several sensing and analytic tasks relevant to CHD, although their performance cannot be assumed to transfer directly to congenital populations.

Related to but distinct from wearable monitoring, AI applied to conventional ECG signals has shown promise for pediatric screening and lifelong CHD risk stratification. AI-ECG approaches have achieved external validation performance for detection of ventricular dysfunction and remodeling in children with AUROC 0.86 to 0.94 and have predicted 5-year mortality across pediatric and adult CHD with AUROC 0.79.[37,38] Although these studies do not establish wearable AI performance directly, they demonstrate that clinically meaningful information can be extracted from cardiovascular signals that are increasingly obtainable through ambulatory and wearable devices.

The strongest patient-outcome evidence for enhanced outpatient surveillance in CHD currently comes from digital home-monitoring programs rather than AI-enabled wearables. In single-ventricle CHD, application-based monitoring of oxygen saturation, heart rate, weight, and temperature after Norwood palliation has been associated with favorable interstage outcomes.[39] Within the CHAMP (Cardiac High Acuity Monitoring Program) system, home video telemetry identified infants at risk for unplanned admission,[35] while a randomized crossover study

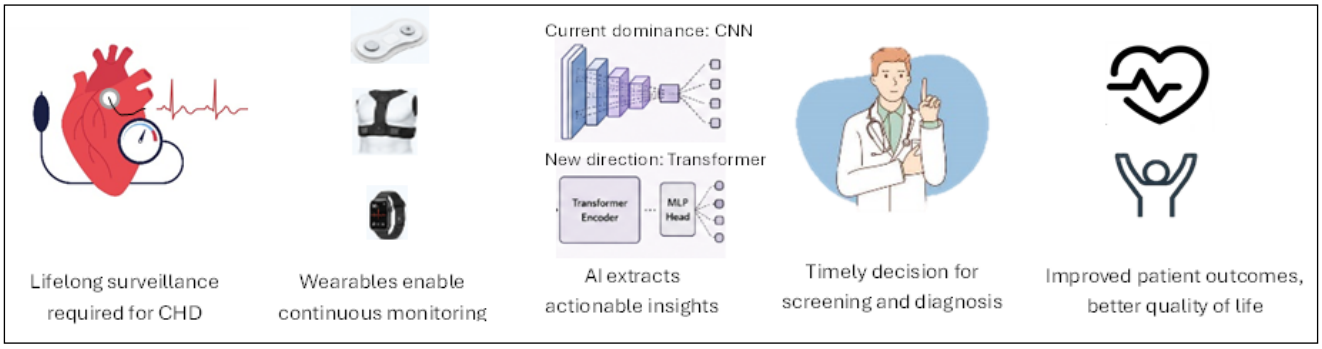


Figure 3 Wearable technologies beyond consumer use: emerging clinical applications and unresolved impact in congenital heart disease (CHD). Given that lifelong surveillance is required for CHD, different forms of wearables used at specific times in a patient's life and focused on clinically relevant parameters may improve disease progression detection. These data need to be analyzed by artificial intelligence (AI) to extract actionable insights, given their scale. The data could then inform timely decisions for disease screening, diagnosis, or progression, leading to improved outcomes.

demonstrated fewer unplanned ICU days, shorter delays in care, and less interstage growth failure than traditional home monitoring.[40,41] These studies establish the clinical value of more frequent surveillance outside the hospital. Wearables offer a logical next step by making such monitoring more continuous, passive, and physiologically rich.

Overall, direct CHD wearable evidence currently supports feasibility and clinically meaningful physiologic measurement, while broader pediatric and adult studies support additional sensing applications. The next step is to determine whether wearable-based monitoring can extend these benefits through more continuous, passive, and scalable surveillance (Table 2).

REGISTRIES: SCALING EVIDENCE GENERATION AND MODEL VALIDATION

Congenital heart disease presents distinct research challenges because it is rare, phenotypically heterogeneous, longitudinal, and highly procedure dependent. Registries provide the scale, nomenclature, benchmarking infrastructure, and follow-up needed to study CHD across the lifespan. The American Academy of Pediatrics has described CHD data as a "complex constellation" distributed across hospitals, specialty societies, and government entities.[42] No single registry captures the full CHD trajectory. Instead, existing registries typically focus on a particular stage of care, patient population, or data modality.

Several major CHD registries serve complementary roles. The Society of Thoracic Surgeons Congenital Heart Surgery Database (STS-CHSD) captures congenital and pediatric cardiac surgery, while the European Congenital Heart Surgeons Association (ECHSA) provides a parallel international surgical registry with standardized nomenclature and cross-center benchmarking.[43,44] The American College of Cardiology - Improving Pediatric and Adult Congenital Treatment (ACC-IMPACT) registry captures congenital catheterization procedures, Pediatric Cardiac Critical Care (PC4) focuses on pediatric cardiac critical care, and the National Congenital Heart Disease Audit (NCHDA) provides national audit infrastructure in the United Kingdom and Ireland.[45-47] Networks such as Single Ventricle Outcomes Network (SV-ONE) and National Pediatric Cardiology Quality Improvement Collaborative (NPC-QIC) focus on single-ventricle outcomes and quality improvement.[48] Lastly, other modality-specific initiatives such as Fontan Outcomes Registry using CMR examinations (FORCE) are focused on clinical outcomes around patients living with Fontan circulation in particular.[49] This specialization enables detailed study within individual stages of care but also fragments information across the patient journey. Cardiac Networks United represents one effort to address this problem by harmonizing data across several congenital cardiovascular networks and supporting research across phases of care.[50]

These registries have already demonstrated that structured CHD data can support benchmarking, risk adjustment, quality improvement, and increasingly predictive modeling. Registry-derived tools have been developed for postoperative and procedural risk assessment, while ECHSA data have been used to train machine-learning models for outcomes including mortality, prolonged ventilation, and length of stay. NPC-QIC data have similarly been used to predict interstage mortality.[51,52] The latter experience is particularly informative: modest predictive performance suggests that conventional registry variables may not fully capture physiologic changes, home-monitoring data, or social context. Together, these studies show that AI applied to CHD registries is already showing value while also highlighting where richer longitudinal data may be needed.

STUDY	POPULATION AND SETTING	AI-ENABLED CLINICAL USE	MAIN FINDING	TRANSLATIONAL STATUS	KEY REMAINING GAP
Bolourchi & Batra, 2015 [34]	National pediatric ambulatory ECG registry, n = 3,209	Extended arrhythmia screening with a 14-day ECG patch; no AI in the primary study	Diagnostic yield was 12.2%; 44% of first-detected arrhythmias occurred after 48 hours	Population-based clinical evidence	Not CHD-specific and observational
Kobel et al., 2022[31]	Prospective study of 215 children with and without CHD	Mobile single-lead ECG acquisition	Recordings were clinically interpretable in 94.9% of cases, although automated rhythm classification was inferior to expert interpretation	Prospective device validation	Limited evaluation of clinically important arrhythmias and pediatric-specific automated interpretation
Ganti et al., 2022[32]	Children and adults with CHD undergoing reference cardiac assessment	Wearable ECG and seismocardiography for stroke-volume estimation	Multimodal wearable features estimated stroke volume with $R^2 = 0.76$ and RMSE = 11.48 mL	CHD-specific feasibility study	Small cohort with no longitudinal deterioration or outcome evaluation
Mayourian et al., 2024[37]	Pediatric CHD across development and external-validation cohorts	Deep-learning ECG detection of ventricular dysfunction and remodeling	Externally validated AUROCs ranged from approximately 0.86 to 0.94	External validation	Based on conventional ECGs rather than continuous wearable acquisition; no prospective clinical deployment
Mayourian et al., 2025[38]	Pediatric and adult CHD across the lifespan	ECG-based prediction of 5-year mortality	AI-ECG predicted mortality with AUROC approximately 0.79 and outperformed several conventional markers	Multicenter retrospective validation	Clinical utility and impact on management have not been prospectively tested
Aly et al., 2021[40]	Infants with single-ventricle physiology enrolled in CHAMP	Video-telemetry warning score for unplanned admission	The warning score predicted unplanned hospital admission with AUROC 0.93	Clinical workflow validation	Digital home monitoring rather than a wearable; requires prospective external validation
Bingler et al., 2018[41]	Infants with single-ventricle physiology, randomized crossover study	Technology-supported interstage home monitoring; no AI	Remote monitoring was associated with fewer unplanned ICU days, shorter delays in care, and less growth failure than binder-based monitoring	Patient-outcome evidence	Small, disease-specific study and no assessment of the incremental contribution of AI
Rosenthal et al., 2025[39]	Infants after Norwood-type palliation, n = 30, with matched and historical comparators	Application-based monitoring of oxygen saturation, heart rate, weight, and temperature	Monitoring completion was 96%, with no interstage deaths in the monitored cohort compared with 14% in matched controls	Prospective observational implementation	Small nonrandomized cohort and no separation of monitoring intensity from technology effect
Zhou et al 2025[33]	Infants with single-ventricle heart disease	Soft chest biopatch + pulse oximetry for at-home monitoring	Soft chest and forehead sensors enabled continuous real-time physiologic data transmission to a cloud platform with automated caregiver alerts	CHD-specific development/ feasibility	No prospective evaluation of whether the system improves clinical outcomes compared with standard interstage home monitoring

Table 2 Wearables-related studies that made use of AI for analysis. The table outlines the study, the application of AI, findings, and the key remaining gap for clinical utility. ECG: electrocardiogram; CHD: congenital heart disease; RMSE: root mean square error; AUROC: area under the receiver operating characteristic curve

The credibility of CHD registries depends on data quality, but maintaining this quality requires substantial human infrastructure. STS-CHSD reported 97.6% completeness and 97.4% agreement for general data elements. PC4 reported 99.1% aggregate accuracy, while ECHSA reported 99% completeness and 89.2% accuracy.[53-55] High-quality abstraction requires trained personnel, standardized definitions, source verification, clinical adjudication, and recurring audits. Broader evaluations report benefit-to-cost ratios of 2:1 to 7:1.[56] However, CHD-specific economic evaluations remain limited and rarely quantify burden per case or field. The key question is whether manual abstraction remains sustainable as CHD care becomes more longitudinal and data intensive.

A separate opportunity is to use AI not only on registry data but also to reduce the burden of creating and maintaining the registry itself. CHD-specific evidence for AI-assisted registry abstraction remains limited, with most developments to date occurring in larger adult cardiac and oncology datasets. However, this disparity primarily reflects the concentration of AI-abstraction development in these larger datasets, not a lack of suitability for CHD applications. Margaritis and colleagues automated abstraction for the STS Adult Cardiac Surgery Database using a hybrid pipeline rather than a purely off-the-shelf LLM.[57] The system combined EHR sources with fine-tuned ClinicalBERT (Bidirectional Encoder Representations from Transformers), Sentence-BERT summarization, TF-IDF (Term Frequency–Inverse Document Frequency) features, and ensemble learning. A dual-threshold framework accepted high-confidence values and deferred uncertain cases to human review. The system achieved greater than 99% accuracy while automatically completing 49.5% and 43.2% of registry variables at two health systems. Lowering the accuracy target to 94% increased potential completion to approximately 75%. This illustrates the tradeoff between automation and registry-grade accuracy. Adult and congenital cardiac registries differ substantially in anatomy and coding complexity, but this work provides an important technical starting point for CHD-specific adaptation and validation.

LLMs also perform well when extracting explicit concepts from semi-structured text. ChatGPT achieved 89% average accuracy for lung cancer pathology variables and near-perfect performance for pediatric osteosarcoma grade and margin status.[58] A privacy-preserving Llama 3.3 70B oncology pipeline achieved F1 scores from 88.1% to 97.2% across registry fields.[59] Across these studies, performance was strongest for explicit, source-grounded fields and declined when abstraction required specialized coding rules, temporal integration, or synthesis across multiple documents. These limitations are particularly relevant to CHD, where a single registry field may depend on anatomy, prior palliation, procedural intent, postoperative events, and later reinterventions.[60,61] The relatively limited CHD-specific abstraction literature therefore represents an opportunity to apply and adapt methods that have already been developed elsewhere rather than a need to start over. Existing adult cardiac and oncology pipelines can provide a foundation for CHD-specific development, while larger congenital datasets will ultimately be needed to determine whether adapted models or models trained directly in CHD perform best.

CHD registries are already mature clinical infrastructure for benchmarking, quality surveillance, and research. AI is beginning to add predictive capabilities within CHD, while the strongest evidence for automated abstraction currently comes from adjacent adult cardiac and oncology domains. Selective automation, in which high-confidence fields are automated while complex longitudinal or anatomy-dependent variables remain under expert review, represents a practical near-term opportunity (Table 3).[57,60]

ROADMAP TO CLINICAL TRANSLATION

The first priority is robust validation in the populations in which these tools are intended to be used. CHD presents particular challenges because anatomy, physiology, age, prior palliation, and clinical trajectories vary substantially among patients. Models developed in broader cardiovascular populations may provide useful starting points, and domain-adaptation methods offer an intermediate strategy by recalibrating models using smaller amounts of CHD-specific data. Such approaches have improved ECG classification across patients, datasets, and recording environments in broader cardiovascular populations.[62-64] Ultimately, performance should be tested across congenital diagnoses, age groups, centers, devices, and imaging or sensor platforms, while larger multicenter CHD datasets are developed to compare adapted general models with models trained specifically in CHD.[65]

Validation of model performance alone will not establish clinical value. Prospective studies must determine whether AI changes care in ways that matter to patients and clinicians. Depending on the application, relevant outcomes may include earlier diagnosis, shorter interpretation or processing time, fewer missed episodes of deterioration, improved treatment decisions, reduced unnecessary testing, or lower registry-abstraction burden. Comparative studies should also assess whether AI-enabled approaches provide incremental benefit over existing clinical workflows rather than simply reproducing information already available to clinicians. Moving from accuracy-based evaluation to impact-based evaluation will be critical for establishing which applications are ready for routine use.[65,66]

Clinical translation will also depend on how AI is integrated into existing workflows. An accurate prediction has limited value if it is delivered at the wrong time, to the wrong user, or without a clear clinical action. Imaging outputs must fit within interpretation workflows, wearable alerts must avoid overwhelming clinicians with false or low-value notifications, and registry automation must preserve source traceability and data quality. Human oversight will therefore remain important, particularly for uncertain, discordant, or high-risk outputs. Selective automation may provide a practical model across these applications—where high-confidence tasks can be automated while ambiguous cases are escalated for expert review. Such systems will also require safeguards

STUDY OR PLATFORM	POPULATION AND SETTING	CLINICAL OR AI-ENABLED USE	MAIN FINDING	TRANSLATIONAL STATUS	KEY REMAINING GAP
STS-CHSD[43,70]	Multicenter congenital surgical registry, 677,684 operations through 2023	Risk adjustment, benchmarking, public reporting, and outcomes research	Enabled national mortality models and longitudinal evaluation of surgical performance	Clinical implementation	Primarily captures surgical episodes and depends heavily on manual abstraction
ECHSA[44,51]	International congenital surgical registry with > 235,000 patients and > 295,000 operations	Machine-learning prediction of mortality, ventilation, and length of stay	Interpretable models achieved AUCs of 0.86, 0.85, and 0.82, respectively	Multicenter registry validation	Focused on surgical outcomes with limited evidence of prospective decision impact
ACC-IMPACT [45,71]	Multicenter pediatric and adult congenital catheterization registry	Procedure-specific risk adjustment and adverse-event prediction	Enabled standardized prediction of major catheterization-related adverse events	Clinical benchmarking infrastructure	Limited to procedural encounters and conventional registry variables
NCHDA and PRAiS[47,72,73]	National congenital procedural audit in the United Kingdom and Ireland	Linked outcomes analysis and real-time risk-adjusted mortality surveillance	PRAiS and VLAD monitoring translated registry data into routine program-level surveillance	Clinical implementation	Nationally specific and centered on short-term procedural outcomes
Cardiac Networks United[50]	Network integrating several pediatric and congenital cardiovascular collaboratives	Harmonization and linkage across stages of CHD care	Provides an organizational framework for aligning data capture across previously separate networks	Implemented data infrastructure	Does not yet represent a single complete longitudinal CHD dataset
Sunthankar et al., 2023[52]	Multicenter NPC-QIC single-ventricle registry	Machine-learning prediction of interstage mortality	Prediction remained modest despite a large registry feature set	Retrospective registry validation	Registry fields may omit dynamic physiology, home-monitoring measures, and social context
Margaritis et al., 2026[57]	STS adult cardiac registry abstraction across two health systems; not CHD-specific	Hybrid NLP and machine-learning pipeline for automated registry abstraction	Achieved > 99% accuracy while automatically completing 43.2%-49.5% of registry fields	Cross-system workflow validation	Preprint, non-CHD population, and only partial field automation
Huang et al., 2024[58]	Lung cancer and pediatric osteosarcoma clinical documentation; not CHD-specific	Off-the-shelf ChatGPT extraction of structured registry variables	Performance was high for explicit fields but errors occurred in staging rules, lymph-node interpretation, and blank reports	Retrospective technical validation	Susceptible to hallucination and failures in domain-specific rule application
Kang et al., 2025[61]	Breast cancer curation across five academic hospitals; not CHD-specific	LLM-assisted longitudinal clinical-data curation	Reduced physician hours by 91% and processing time from seven months to 12 days	Multicenter workflow evaluation	More missing staging data and weaker integration of sequential procedures

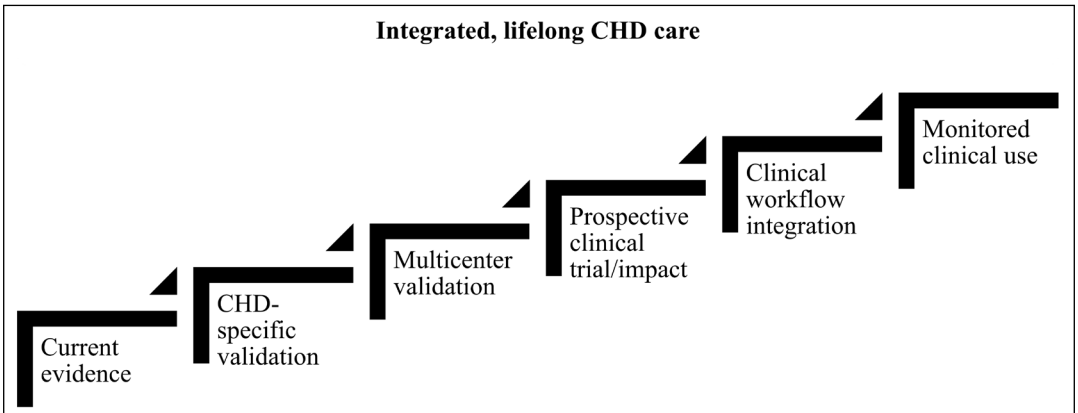
Table 3 Examples of clinical and research registries used in congenital heart disease and other fields. The table outlines the study, the application of AI, findings, and the key remaining gap for clinical utility. AUC: area under the curve; PRAiS: Prospective Randomized Amlodipine Survival Evaluation; VLAD: Variable Life-Adjusted Display; CHD: congenital heart disease; NPC-QIC: National Pediatric Cardiology Quality Improvement Collaborative; STS: Society of Thoracic Surgeons; NLP: natural language processing; LLM: language learning model

against automation bias, alert fatigue, and gradual degradation in performance after deployment.[65-67]

Regulatory and implementation considerations are equally important. AI systems must be evaluated for performance drift, device and vendor dependence, privacy, and accountability as they move from research into clinical use. Bias may be particularly consequential in CHD because rare lesions, younger children, and patients with complex surgical histories can be underrepresented even within congenital datasets. Access also matters because wearable devices, remote monitoring platforms, and advanced imaging tools could widen disparities if their use depends on digital literacy, reliable connectivity, or resources unavailable to some patients.[63,64] Clinical implementation should therefore include subgroup-specific performance assessment, continued post-deployment monitoring, and deliberate evaluation of whether new technologies improve rather than redistribute existing inequities (Figure 4).[65,68]

DISCUSSION

Taken together, imaging, wearables, and registries provide complementary rather than competing foundations for AI in CHD. Imaging provides detailed but episodic information about anatomy and function; wearable and remote-monitoring technologies extend physiologic observation beyond clinical encounters; and registries provide longitudinal



DOMAIN	CURRENT STATUS	KEY NEXT STEP
Imaging	Evidence strongest for disease detection and CMR segmentation	Validate broader imaging AI approaches specifically in CHD and assess clinical usefulness
Wearables	Feasibility for rhythm and physiologic monitoring	Determine whether continuous, passive wearable monitoring can improve longitudinal CHD surveillance
Registries	CHD registries are well established, but automated abstraction is less developed	Validate AI-assisted abstraction in CHD while maintaining registry-level accuracy

Figure 4 Roadmap for clinical translation of artificial intelligence in congenital heart disease. AI: artificial intelligence; CHD: congenital heart disease; CMR: cardiac magnetic resonance

structure, standardized outcomes, and population-level scale. The greatest opportunity may therefore lie not only in improving each data stream independently but in connecting information across the CHD lifespan.

This integration also creates new challenges. Errors, missingness, or bias in one data source may propagate when multiple sources are combined, while increasing model complexity can make clinical interpretation more difficult. AI development in CHD should therefore remain anchored to clearly defined clinical questions rather than model architecture alone. Success should be judged not only by improvements in technical performance but by whether these systems extend specialist capability, identify clinically meaningful change, reduce avoidable workload, or improve patient outcomes.

CONCLUSION

Ultimately, the successful translation of AI in CHD will depend less on any single algorithm than on the quality, integration, and clinical relevance of the data that support it. Imaging, wearables, and registries offer complementary pathways to improve care across the lifespan, but each will require rigorous CHD-specific validation, equitable implementation, and sustained clinical oversight. Progress will therefore depend on close collaboration among clinicians, engineers, researchers, patients, and health systems to ensure that AI strengthens rather than fragments lifelong CHD care.

KEY POINTS

- Congenital heart disease (CHD) is characterized by heterogeneity, specialized care needs, and lifelong clinical management.
- Current artificial intelligence (AI) research in CHD remains limited by small cohorts, single-center studies, under-representation of diverse CHD phenotypes, fragmented evidence, and lack of standardized approaches for data collection.
- Current evidence remains strongest in imaging technologies, while wearables provide a promising path for longitudinal monitoring but remain under-validated in CHD-specific populations.
- Future AI research should leverage imaging as the current reference standard, strengthen wearable-based continuous monitoring, and connect registries to support integrated, longitudinal approaches in CHD.

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