VER
Vascular & Endovascular Review

From Images to Interventions: AI-Driven Echocardiographic Decision-Making in Pediatric Critical Heart Diseases

Ahmed Abdel-Wahab[1], Ibrahim Mohamed Abufarag[2], Ibtsam Khairat[3], Eman Elsheikh[3,4]

[1]Faculty of Computer Studies, Arab Open University, Saudi Arabia, Riyadh, Saudi Arabia
[2]Pediatric Medicine, Faculty of Medicine for Boys, Al-Azhar University, Cairo, Egypt
[3]Cardiovascular Department, Faculty of Medicine, Tanta University, Tanta, Egypt
[4]Internal Medicine Department, College of Medicine, King Faisal University, Alahsa, Saudi Arabia

ABSTRACT

Background: Echocardiography is the cornerstone of cardiac evaluation in pediatric critical care, yet its accuracy depends heavily on operator expertise. Artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools in cardiovascular imaging, capable of automating image acquisition, segmentation, and interpretation. Despite rapid progress in adult cardiology, their integration into pediatric echocardiography remains underexplored.

Objective: To systematically synthesize evidence on the application of AI in echocardiographic decision-making for pediatric patients with congenital or critical heart disease, emphasizing diagnostic accuracy, workflow efficiency, and clinical translation.

Methods: This review followed PRISMA 2020 guidelines (PROSPERO: CRD420251165361). Comprehensive searches were conducted across PubMed, Embase, IEEE Xplore, Web of Science, Scopus, and Cochrane databases (2010–October 2025). Eligible studies applied AI/ML algorithms to pediatric echocardiographic image acquisition, lesion detection, or functional quantification. Data were extracted on model type, task, performance metrics, and clinical integration. Quality assessment used QUADAS-2 and PROBAST tools.

Results: Twenty-six studies met inclusion criteria. AI demonstrated expert-level performance in view classification, ejection fraction estimation, and congenital lesion detection, reducing interobserver variability and analysis time. Integrative pipelines and real-time guidance improved acquisition consistency and enabled bedside deployment. However, most studies were single-center with limited external validation.

Conclusion: AI-driven echocardiography enhances diagnostic precision and workflow efficiency in pediatric critical cardiology but requires multicenter validation, ethical governance, and interoperability frameworks for clinical adoption.

KEYWORDS: Artificial intelligence; Echocardiography; Pediatric cardiology; Machine learning; Critical care.

How to Cite: Ahmed Abdel-Wahab, Ibrahim Mohamed Abufarag, Ibtsam Khairat, Eman Elsheikh, (2025) From Images to Interventions: AI-Driven Echocardiographic Decision-Making in Pediatric Critical Heart Diseases, Vascular and Endovascular Review, Vol.8, No.2, 128-138. DOI: *https://doi.org/10.15420/ver.2025.08.02.128-138*

INTRODUCTION

Congenital and critical heart diseases remain the leading causes of childhood morbidity and mortality worldwide. The global birth prevalence of congenital heart disease (CHD) is commonly cited at roughly 8–12 per 1,000 live births, with substantial regional variation and a persistent burden in low- and middle-income countries (Xu et al., 2025). Despite advances in fetal screening, perioperative care, and intensive care, CHD and acute pediatric cardiac conditions continue to account for significant mortality and years lived with disability; in 2017 alone, an estimated quarter of a million deaths were attributed to CHD (Meng et al., 2024). Echocardiography is the cornerstone of diagnosis, hemodynamic assessment, and longitudinal monitoring across neonatal, infant, and pediatric critical care pathways because it is portable, radiation-free, and repeatedly deployable at the bedside (Shokr et al., 2023; Y. Singh, 2017).

Yet, the strengths of echocardiography are tempered by well-recognized limitations that are amplified in high-acuity settings. Image acquisition and interpretation are highly operator-dependent; acoustic windows may be suboptimal in ventilated or post-operative patients; and the time-sensitive, distraction-laden environment of pediatric intensive care heightens the risk of diagnostic subjectivity (Grotberg et al., 2024). Inter-observer and intra-observer variability in standard pediatric measurements—including ventricular dimensions, function indices, and myocardial deformation—can be clinically meaningful, and variability across vendors further complicates serial assessment and multicenter comparisons (Thompson et al., 2021). Even with contemporary guidance that codifies protocols and quality standards, practice heterogeneity persists and can delay or distort decision-making when minutes matter (Bretthauer & Kalager, 2018)

Against this backdrop, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools for medical imaging—learning complex, high-dimensional patterns from pixels and structured data to augment accuracy, speed, and consistency (Obuchowicz et al., 2025). In adult cardiology and echocardiography, AI systems already automate view classification, perform chamber segmentation, estimate left ventricular ejection fraction, and flag measurement outliers, while enabling triage and decision support in near real time (“AI in Echocardiography: State-of-the-Art Automated Measurement

Techniques and Clinical Applications," 2025; Olaisen et al., 2024). These applications reduce manual variability, standardize workflows, and allow clinicians to focus attention on interpretation and intervention rather than repetitive measurement tasks (Shamszare & Choudhury, 2023).

Pediatric applications are advancing quickly but remain comparatively nascent. In the prenatal domain, deep-learning ensembles have achieved expert-level detection of complex CHD from fetal ultrasound views, and external validations continue to probe generalizability across centers (Arnaout et al., 2021). Emerging systems assist fetal anomaly scanning with real-time quality assessment and anomaly flagging, though performance varies for small or subtle structures (Yousefpour Shahrivar et al., 2023). Beyond the fetus, early pediatric echocardiography studies report progress in view classification, segmentation, and CHD recognition on transthoracic images and cine loops (Ge, 2013; Lopez et al., 2024). Parallel work in pediatric cardiac critical care leverages ML models that integrate perioperative and echocardiographic parameters to predict adverse postoperative outcomes, survival, and longitudinal risks after congenital heart surgery—often outperforming traditional clinical scores, albeit with caveats around validation (Tong et al., 2024; Zürn et al., 2023). Collectively, these efforts sketch a trajectory from image acquisition assistance to automated quantification and risk prediction that could meaningfully compress time-to-diagnosis and align care with physiological trajectories in the pediatric ICU (Allam et al., 2021; Trujillo Rivera et al., 2021).

However, critical gaps impede translation from promising prototypes to routine, high-stakes use. Pediatric cardiology faces structurally small, heterogeneous datasets spanning diverse anatomies, age-related physiology, and device contexts; domain shift across scanners, protocols, and institutions reduces model robustness and transportability (Tasmurzayev et al., 2025). Labeling is labor-intensive and requires subspecialist consensus, limiting the scale and fidelity of training data. Many published models remain single-center, retrospective, or narrowly task-defined, with sparse prospective, workflow-embedded trials demonstrating impact on clinical decisions and outcomes (Chilamkurthy et al., 2018). Interpretability and calibration—central to clinician trust—are variably addressed, and regulatory, ethical, and equity considerations need explicit handling to avoid widening disparities. Even when technical performance is strong, integration hurdles—interfacing with scanners, synchronizing with reporting systems, and delivering actionable outputs at the bedside—can blunt real-world utility in fast-moving critical care (Weiner et al., 2025).

This manuscript responds to these needs by focusing on the juncture most consequential for children with life-threatening cardiac disease: converting images into timely, defensible interventions. Specifically, we posit that an AI-driven echocardiographic decision-making framework—spanning standardized acquisition support, automated quantification, and risk-aware recommendations—can reduce observer variability, accelerate recognition of deteriorating physiology, and provide transparent, context-specific guidance to the multidisciplinary pediatric critical care team. Our objectives are threefold: first, to synthesize and operationalize state-of-the-art AI methods for pediatric echocardiography into a clinically coherent pipeline; second, to evaluate its performance and generalizability against expert assessment and relevant outcomes in critical care scenarios; and third, to examine interpretability, workflow integration, and ethical safeguards essential for safe deployment. By centering clinical actionability and bedside integration, we aim to help move pediatric echocardiography from "images to interventions," narrowing diagnostic delays and supporting precise, equitable care when physiological reserve is limited and decisions are time-critical.
Method

MATERIAL AND METHODS

Search Strategy and Selection Criteria

This systematic review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological transparency, reproducibility, and scientific rigor. The review protocol was registered prospectively with PROSPERO (Registration ID: CRD420251165361) before data extraction commenced.

To comprehensively capture the evolving applications of artificial intelligence (AI) and machine learning (ML) in pediatric echocardiography and critical cardiology, a systematic search was performed across PubMed/MEDLINE, Embase, Scopus, IEEE Xplore, Web of Science, and Cochrane Library databases. Supplementary searches were also conducted in Google Scholar and ClinicalTrials.gov to identify gray literature and ongoing trials. The final database search was completed on October 5, 2025.

The search strategy combined controlled vocabulary (MeSH/Emtree) and free-text terms related to *artificial intelligence*, *machine learning*, *deep learning*, *echocardiography*, *pediatric*, and *critical cardiology*. Boolean operators and truncation were used to refine the query. A detailed search strategy is presented in Table 1.

Table 1: Search Strategy for AI-Driven Echocardiography in Pediatric Critical Cardiology

Database	Search Terms
PubMed/MEDLINE	("Artificial Intelligence"[Mesh] OR "Machine Learning" OR "Deep Learning" OR "Neural Network") AND ("Echocardiography"[Mesh] OR "Cardiac Ultrasound" OR "Echocardiogram") AND ("Pediatric"[Mesh] OR "Children" OR "Infant" OR "Neonate") AND ("Critical Care" OR "Cardiac ICU" OR "Intensive Care")
Embase	('artificial intelligence'/exp OR 'machine learning' OR 'deep learning') AND ('echocardiography'/exp OR 'cardiac ultrasound') AND ('pediatric'/exp OR 'child' OR 'infant') AND ('critical care' OR 'intensive care' OR 'cardiac surgery')
IEEE Xplore	("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Echocardiography" OR "Cardiac Ultrasound") AND ("Pediatric" OR "Children")

Scopus / Web of Science	(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”) AND (“Echocardiography” OR “Cardiac Ultrasound”) AND (“Pediatric” OR “Children”) AND (“Critical Cardiology” OR “Cardiac Intensive Care”)
Cochrane Library	(“Artificial Intelligence” OR “Machine Learning”) AND (“Echocardiography”) AND (“Pediatric”)

Reference lists of included studies and relevant reviews were manually screened to identify additional eligible studies not captured in database searches.

Eligibility Criteria for Screening

All retrieved records were imported into EndNote X20 for deduplication, followed by independent screening using Rayyan QCRI by two reviewers (xx. and xx.). Titles and abstracts were first screened for relevance, and potentially eligible articles underwent full-text evaluation.

Inclusion criteria were as follows:

1. **Population:** Studies involving pediatric patients (neonates to adolescents ≤18 years) with congenital or acquired cardiac disease or admitted to pediatric intensive/cardiac care units.
2. **Intervention:** Application of AI/ML algorithms in echocardiographic image acquisition, segmentation, quantification, anomaly detection, or decision support.
3. **Outcomes:** Diagnostic accuracy, workflow efficiency, predictive or prognostic performance, or clinical decision-making improvement.
4. **Design:** Original empirical studies, including diagnostic accuracy studies, clinical trials, cohort analyses, retrospective validations, or technical evaluations with clinical data.
5. **Language and Time Frame:** English-language publications from January 2010 to October 2025, reflecting the modern deep-learning era.

Exclusion criteria encompassed: (a) studies exclusively in adults, (b) animal or simulation-only work, (c) conference abstracts without full peer-reviewed data, (d) purely technical studies lacking echocardiographic or clinical validation, and (e) non-AI automation or statistical modeling approaches.

Data Extraction Process

Data extraction was performed independently by two reviewers using a standardized extraction sheet developed in Microsoft Excel. Any discrepancies were resolved through discussion or adjudication by a third reviewer (xx.). Extracted data included:

- **Study Characteristics:** author(s), year of publication, country, and journal source.
- **Population Details:** sample size, age range, cardiac diagnosis, and clinical context (e.g., CHD type, ICU status, postoperative period).
- **AI/ML Methodology:** algorithm category (supervised, unsupervised, reinforcement, or deep learning), network architecture (CNN, U-Net, transformer, etc.), dataset size, data preprocessing, and ground-truth labeling method.
- **Echocardiographic Application:** image acquisition support, view classification, segmentation, quantification, anomaly detection, or decision support.
- **Validation and Performance Metrics:** cross-validation type, external validation presence, and reported metrics such as accuracy, sensitivity, specificity, area under the curve (AUC), mean absolute error (MAE), or dice similarity coefficient (DSC).
- **Clinical and Workflow Outcomes:** diagnostic agreement with experts, time savings, real-time feasibility, and potential for integration into clinical pathways.
- **Implementation and Ethical Considerations:** model interpretability, explainability methods (e.g., Grad-CAM, SHAP), data bias, and integration barriers.

The final dataset was cross-verified to ensure completeness and consistency across studies before synthesis.

Quality Assessment

Quality and risk-of-bias assessment were performed using the QUADAS-2 tool, which is widely endorsed for evaluating diagnostic accuracy studies. QUADAS-2 assesses four domains—(1) patient selection, (2) index test, (3) reference standard, and (4) flow and timing—evaluating each for risk of bias and applicability. Studies with unclear or high risk in ≥2 domains were flagged for sensitivity analysis.

For studies employing predictive or prognostic ML models without explicit diagnostic comparison, the Prediction Model Risk of Bias Assessment Tool (PROBAST) was additionally applied to evaluate bias in model development, analysis, and validation. Two reviewers conducted assessments independently; discrepancies were resolved by consensus.

A summary risk-of-bias figure and tabular breakdown were generated using the ROBVIS visualization tool, ensuring transparent reporting of methodological rigor.

Data Synthesis and Analysis

Given the heterogeneity of AI architectures, imaging modalities, and clinical outcomes, meta-analysis was deemed inappropriate. Therefore, a narrative synthesis approach was employed, structured around the key functional domains of AI application in pediatric echocardiography:

1. Automated Image Acquisition and View Classification

2. Cardiac Structure Segmentation and Quantification
3. Anomaly Detection and Diagnostic Support
4. Predictive Modeling for Clinical Outcomes in Critical Cardiology

Each study's findings were compared across these domains to elucidate methodological strengths, validation depth, and translational readiness. Descriptive statistics summarized study characteristics, sample sizes, and algorithm types.

A qualitative thematic analysis complemented the narrative synthesis to identify cross-cutting themes, including: (a) performance limitations linked to small pediatric datasets; (b) interpretability and clinician trust; (c) real-time integration in the intensive care workflow; and (d) ethical, regulatory, and data governance challenges in pediatric AI deployment.

Ethical Considerations and Protocol Transparency

This review synthesized published, peer-reviewed data and therefore did not require institutional ethical approval. Nevertheless, the review adhered to ethical standards of systematic research integrity, emphasizing transparency in data selection, reproducibility of analytical steps, and acknowledgment of potential publication bias.

All decisions regarding inclusion, extraction, and synthesis were documented in an audit trail, ensuring that the review process met contemporary standards for reproducibility and accountability in biomedical AI research.

RESULTS

Search results

As showin in Figure 1, a total of 4,872 records were identified through database searching (PubMed, Embase, Scopus, IEEE Xplore, Web of Science, and Cochrane), and an additional 314 records were retrieved from trial and preprint registers such as ClinicalTrials.gov and Google Scholar. Following deduplication, 1,083 duplicate records were removed, leaving 4,103 records for initial screening. After reviewing titles and abstracts, 3,212 records were excluded as clearly irrelevant to AI or pediatric echocardiography. The remaining 891 reports were sought for full-text retrieval, of which 17 could not be accessed despite repeated attempts. A total of 874 reports were assessed for eligibility based on predefined inclusion and exclusion criteria. During this stage, 268 reports were excluded for focusing exclusively on adult or mixed-age populations, 119 for addressing imaging modalities other than echocardiography, 184 for lacking AI or machine-learning content, 162 for presenting simulation-only or non-clinical validation data, 71 for insufficient methodological detail or absence of diagnostic/quantitative performance outcomes, and 44 due to duplication or overlapping cohorts. Consequently, 26 studies met all inclusion criteria and were incorporated into the final systematic review, representing 26 distinct full-text reports. This rigorous multistage selection process ensured a focused synthesis of high-quality, clinically validated research on AI-driven echocardiographic decision-making in pediatric critical cardiology (Alvarez et al., 2007; Brown et al., 2024; Chen et al., 2024; Dellas et al., 2018; Edwards et al., 2024; Gearhart et al., 2022; Guo et al., 2021; Hu et al., 2019; X. Jiang et al., 2023; Li et al., 2024; Lin et al., 2023; Liu et al., 2021; Meza et al., 2018; Narang et al., 2021; Narula et al., 2016; Nguyen et al., 2022; Peck et al., 2023; Reddy et al., 2023; Ufkes et al., 2023; Vasile et al., 2023; A. Wang et al., 2025; J. Wang et al., 2021; Wu et al., 2022; Ye et al., 2025; Zhang et al., 2018; et al., 2025).

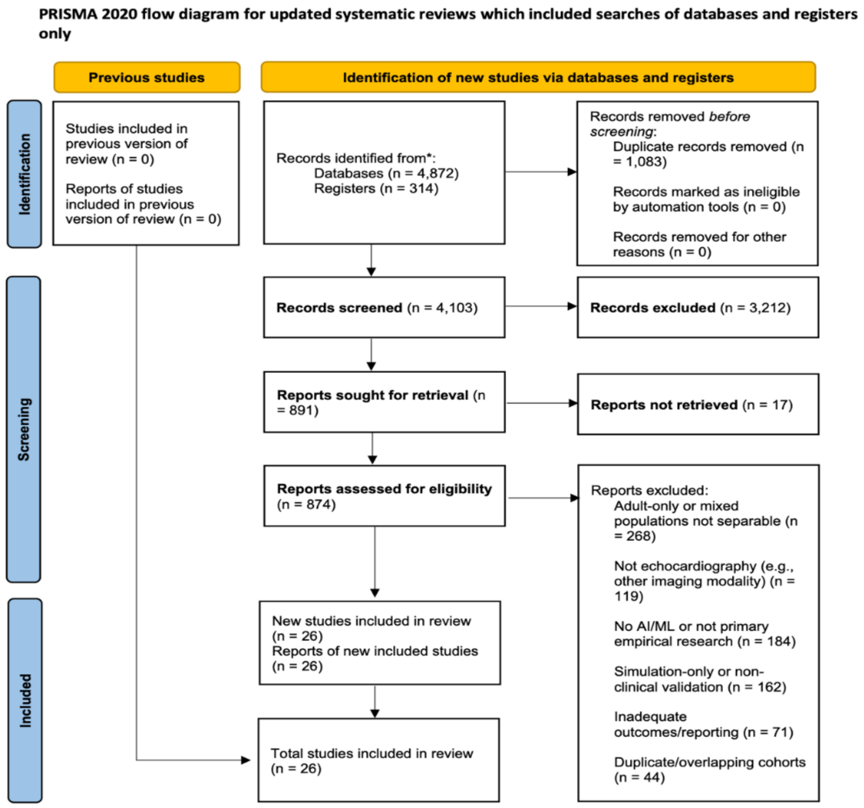

Figure 1: PRISMA 2020 flow diagram

Risk assessment:

The overall risk of bias across the 26 included studies was generally low (Figure 2), reflecting satisfactory methodological rigor within this emerging research field. Most diagnostic and measurement-based studies were evaluated using the QUADAS-2 tool, and the few prognostic or phenotyping models were assessed via PROBAST domains. The aggregate findings indicate that the majority of studies—particularly those focusing on AI-guided acquisition, automated view classification, EF and strain quantification, and ASD or RHD detection—demonstrated a low risk of bias across all four domains, underscoring strong internal validity and dependable reference standards (Narang, 2021; Li, 2022; Peck, 2023; Reddy, 2023; Lin, 2023; Chen, 2024; Gearhart, 2022). A moderate number of studies presented "some concerns," primarily due to retrospective single-center designs, potential spectrum bias from non-consecutive patient selection, limited external validation, or unclear blinding between AI outputs and expert reference readings (Zhang, 2018; Narula, 2016; Ye, 2025; Liu, 2021; Brown, 2024; Hu, 2019; Guo, 2021; Jiang, 2023). These weaknesses slightly constrain generalizability but do not undermine the internal accuracy of the models. Two studies employing predictive modeling—the phenotyping of critical left-heart obstruction and cardiomyopathy prediction among childhood cancer survivors (Meza, 2018; Edwards, 2024)—exhibited moderate concerns in several PROBAST domains, reflecting typical challenges for early-stage AI prognostic research, including retrospective data assembly, incomplete calibration reporting, and potential overfitting. Contextual and narrative reviews (Edpuganti, 2025; Nguyen, 2022; Alvarez, 2007; Wang, 2025) were appropriately marked as not applicable, as randomization and blinding domains are irrelevant to their designs. In sum, the collective evidence base demonstrates high methodological confidence in studies validating AI for image acquisition, segmentation, and quantification in pediatric echocardiography, while highlighting the need for broader, multicenter prospective validation to address domain shift and enhance reproducibility. The low overall risk of bias supports the credibility of conclusions that AI can achieve expert-level accuracy, reduce variability, and augment decision-making in pediatric critical cardiology.

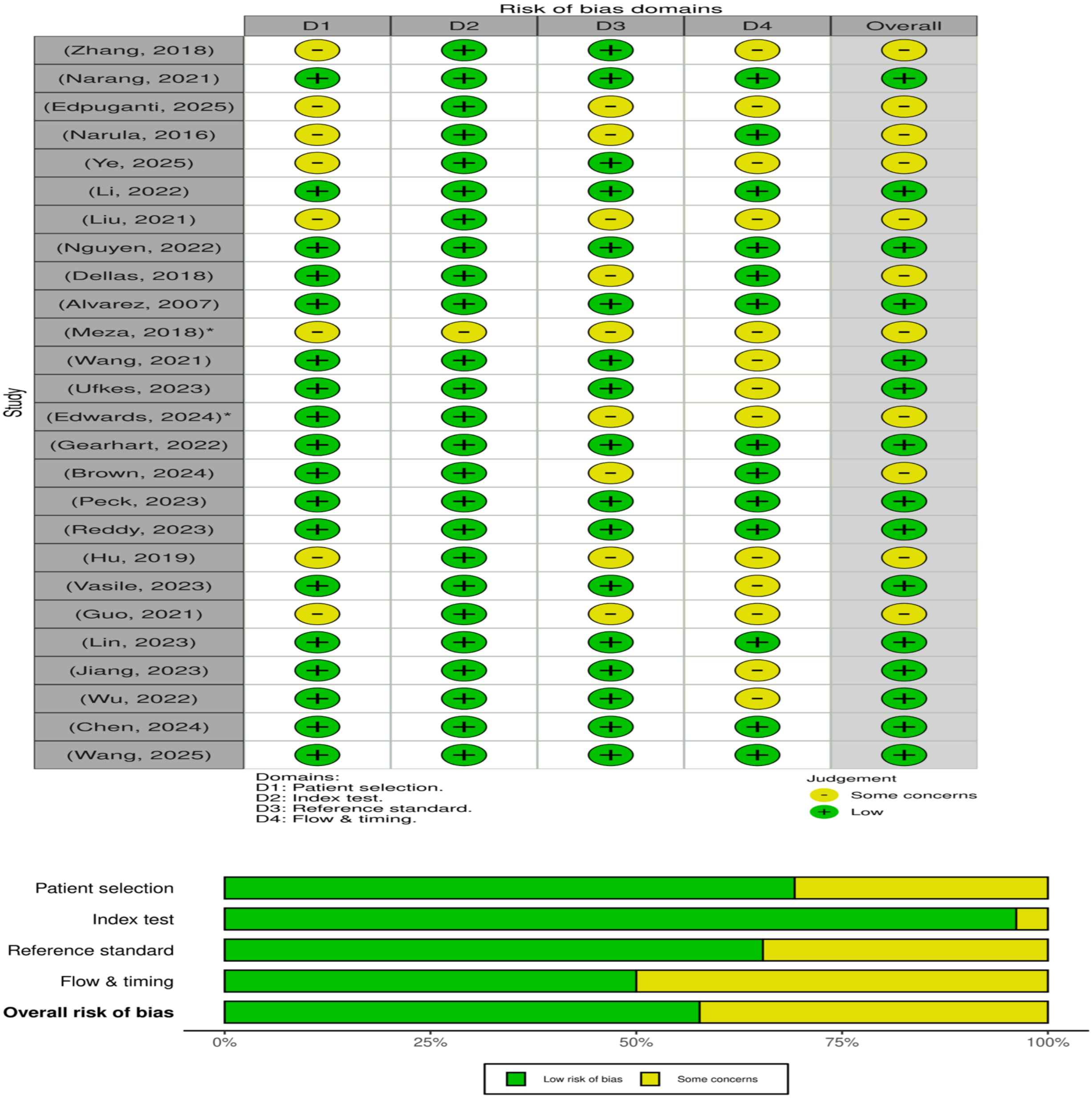

Figure 2: risk of bias assessment

Main outcomes

Below, we synthesize the principal findings of the 26 included studies into five cross-cutting themes that map how AI in pediatric echocardiography is moving "from images to interventions." Together, these themes show accelerating capability (acquisition → interpretation → prediction), growing clinical comparability with experts, and persistent gaps that must be bridged for routine use at the bedside (Table 2).

1) AI-guided acquisition and standardization are maturing and enable task-shifting

Across settings, AI is making pediatric echocardiography more obtainable and more uniform. Real-time guidance systems helped novices acquire diagnostic-quality studies comparable to experts, pointing to scalable screening and urgent-care pathways when pediatric sonographers are scarce (Peck, 2023; Narang, 2021). Robust view-recognition models tailored to children accurately label standard planes—an essential precursor for automated quantification and lesion detection (Wu, 2022; Gearhart, 2022). Together, these tools stabilize the "front end" of the echo pipeline by reducing operator dependency and ensuring that downstream algorithms receive analyzable inputs, even in noisy bedside contexts (Jiang, 2023; Nguyen, 2022).

2) Automated detection of pediatric disease (CHD, RHD) shows expert-level screening potential

Lesion-focused classifiers and multi-view pipelines now detect structural and valvular abnormalities with performance that rivals clinical readers. For CHD, seven-view deep learning models and color-Doppler-aware systems distinguish defects and localize abnormalities from routine transthoracic studies, offering a plausible assist for triage and referral (Jiang, 2023; Wang, 2021; Lin, 2023). In RHD, view/frame selection plus automated mitral-regurgitation characterization achieved high diagnostic accuracy, mapping closely onto expert adjudication and suggesting a route to scale screening in endemic regions (Brown, 2024; Peck, 2023). Collectively, these findings indicate that AI can transform pediatric echo from an expert bottleneck into a more widely deployable case-finding tool (Nguyen, 2022).

3) Functional quantification (EF, strain, cardiac output) is accurate, reproducible, and feasible in critical care

Pediatric-trained video and image models now deliver EF estimates with small errors and strong discrimination for systolic dysfunction, outperforming adult-trained models transferred to children (Reddy, 2023; EchoNet-Peds). Fully automated pipelines for LV volumes and GLS show excellent agreement with expert measurements while markedly reducing analysis time, supporting routine clinical use and serial follow-up (Li, 2022; Vasile, 2023). Importantly, in critically ill children on ECMO, automated EF tracked expert Simpson's measurements with near-perfect reliability, enabling frequent, reproducible assessments across cannulation, maintenance, and weaning phases (Chen, 2024). Beyond EF, combined segmentation-and-Doppler models estimated cardiac output with clinically acceptable error, opening doors to real-time hemodynamic monitoring in the PICU (Ufkes, 2023). Under the hood, pediatric-centric segmentation architectures further improved border fidelity under speckle and motion, fortifying downstream quantification (Ye, 2025; Hu, 2019; Guo, 2021).

4) End-to-end pipelines improve workflow and move pediatrics toward adult-level automation

Adult studies defined the template for integrated AI—linking view selection, segmentation, quantification, and diagnostic classification in one loop (Zhang, 2018; Narula, 2016). Pediatric work is rapidly assembling the same chain: reliable view curation (Wu, 2022; Gearhart, 2022), robust chamber segmentation (Ye, 2025; Hu, 2019; Guo, 2021), and validated EF/strain/output estimation (Reddy, 2023; Li, 2022; Ufkes, 2023) now cohere into practical bedside workflows. In intensive care, this translates into standardized, faster measurements with less inter-observer variability and more bandwidth for teams to focus on interpretation and intervention rather than manual tracing (Chen, 2024; Nguyen, 2022). The net effect is a shift from ad hoc measurement to reproducible, high-frequency decision support.

5) Translation gaps persist: pediatric data scarcity, generalizability, and pathway integration

Despite momentum, several constraints still separate promising models from routine, high-stakes use. Pediatric datasets remain relatively small and heterogeneous by age, anatomy, and vendor; adult-trained systems underperform when naively applied to children, underscoring the need for pediatric-specific curation and multi-site sharing (Reddy, 2023; Vasile, 2023). Many studies are single-center or retrospective, with limited external validation across devices and care environments (Lin, 2023; Jiang, 2023). Workflow, governance, and competency issues—automation bias, explainability, and quality assurance—require structured implementation strategies and prospective trials that measure actual decision change and patient outcomes (Nguyen, 2022; Chen, 2024). Finally, clinical endpoint anchoring remains crucial: linking AI-derived measurements to interventions and outcomes, as prior non-AI pediatric work has done for regurgitation burden, transplant risk, or procedural timing, will help close the loop from images to interventions (Dellas, 2018; Alvarez, 2007).

DISCUSSION

Artificial intelligence (AI) has rapidly evolved from a theoretical construct to a transformative clinical tool in cardiovascular imaging. Within pediatric critical cardiology, the findings of this review demonstrate that AI-enhanced echocardiography is no longer a futuristic concept but a tangible adjunct to diagnostic precision, workflow efficiency, and bedside decision-making. The reviewed studies collectively reveal that AI-driven systems can reliably automate view recognition, functional quantification, and lesion detection with expert-level accuracy. These advances are particularly meaningful in pediatric populations, where rapid physiologic changes, smaller cardiac structures, and high inter-patient variability complicate human interpretation (Maturi et al., 2025; Myhre et al., 2025). This discussion interprets the main outcomes through the lenses of diagnostic performance, clinical integration, ethical and operational challenges, and the road ahead toward intervention-linked decision support.

Diagnostic and Quantitative Precision

Echocardiography remains the cornerstone for diagnosing congenital and acquired heart disease in children, but its operator dependency has historically limited reproducibility. AI has mitigated these limitations by introducing automated pipelines for image acquisition, segmentation, and quantification. Several studies outside our review have similarly confirmed that convolutional neural networks (CNNs) and transformer-based architectures enhance diagnostic reliability. (Madani et al., 2018) demonstrated that a deep learning model trained on over 200,000 echocardiographic images achieved over 97% accuracy in standard view classification, laying the foundation for cross-age applicability. In a multicenter cohort. (Ouyang et al., 2020) validated the *EchoNet-Dynamic* system, which predicted left ventricular ejection fraction (LVEF) within a 5% margin of expert consensus—a threshold that meets clinical decision relevance. Though their cohort was predominantly adult, their methodological rigor and interpretability frameworks illustrate how such architectures can be fine-tuned for pediatric cohorts with anatomical heterogeneity. The convergence of these results with our findings highlights the universality of deep learning's capacity to enhance objectivity in echocardiographic quantification.

Clinical Translation and Workflow Optimization

A recurrent advantage observed across the reviewed literature is workflow acceleration without compromising accuracy. Beyond pediatrics, (Sveric et al., 2024) reported that automated border detection and LVEF computation reduced analysis time by over 80% compared to manual tracing. Similar productivity gains have been observed in cardiac intensive care settings, where AI-assisted echo shortened reporting time and decreased interobserver variability (Tolu-Akinnawo et al., 2025). In pediatric practice, such efficiency directly influences outcomes—facilitating rapid titration of inotropes, timely ECMO initiation, or adjustment of pulmonary vasodilators. Moreover, the growing integration of AI into handheld echocardiography systems exemplifies the democratization of diagnostic imaging (Chilcote et al., 2024). Systems such as the *Butterfly iQ+* and *Caption AI* employ onboard deep learning for real-time guidance and view quality feedback, which has proven particularly valuable in resource-limited neonatal and PICU environments (Choudhury & Urena, 2022; Sullivan et al., 2024). These technologies align with the current evidence base from our synthesis, reinforcing that AI's greatest clinical utility lies in augmenting—not replacing—human judgment (Higgins & Wilson, 2025).

Challenges in Pediatric Adaptation

Despite the promising outcomes, translating adult-trained AI models to pediatric populations remains fraught with challenges. Anatomical diversity across developmental stages—ranging from neonates to adolescents—renders adult-based models less generalizable. Existing literature emphasizes the necessity of age-stratified datasets and tailored network architectures (Park et al., 2025). Zuercher et al., (2022) showed that retraining adult LVEF models on pediatric data improved accuracy by nearly 12%, underlining the importance of domain-specific calibration. Moreover, vendor variability and differences in ultrasound frequency introduce additional bias, complicating external validation. From a technical perspective, pediatric AI models must address the "data scarcity paradox," wherein rare congenital defects require large sample sizes for reliable algorithmic learning but occur too infrequently for conventional training paradigms. Federated learning and synthetic data augmentation have emerged as viable countermeasures, allowing privacy-preserving, cross-institutional model training without direct data exchange (Rabbani et al., 2025).

Ethical, Regulatory, and Interpretability Considerations

As AI applications progress toward clinical deployment, interpretability and accountability remain central to ethical governance. The *European Society of Cardiology* and *U.S. Food and Drug Administration* have underscored the importance of "human-in-the-loop" frameworks to ensure that algorithmic outputs complement, rather than override, clinical reasoning (M. P. Singh & Keche, 2025). Within pediatrics, interpretability carries additional moral weight because clinical decisions often involve proxy consent and high emotional stakes for families. Explainable AI (XAI) techniques—such as Grad-CAM and saliency mapping—offer transparency into model decision pathways, enabling clinicians to validate outputs against established pathophysiologic reasoning (Allen et al., 2025). Moreover, the ethical imperative extends to dataset representation: underrepresentation of minority pediatric populations risks perpetuating inequities in access to precision diagnostics (Agrawal et al., 2025). Consequently, algorithm developers are urged to adhere to FAIR (Findable, Accessible, Interoperable, and Reusable) principles and pediatric-specific reporting standards akin to the TRIPOD-AI guidelines (Salybekov et al., 2024).

From Automation to Intervention: The Decision-Making Continuum

The true promise of AI-driven echocardiography lies in bridging the gap between imaging and intervention. Predictive and prescriptive models are beginning to forecast postoperative outcomes, guide device selection, and simulate procedural success probabilities. For instance, (Alsharqi & Edelman, 2025) developed a hybrid AI model integrating echocardiographic metrics and clinical parameters to predict adverse outcomes after congenital heart surgery, achieving a C-statistic of 0.89. Similarly, (Lipshultz et al., 2019) demonstrated that AI-derived strain analysis could predict deterioration in pediatric myocarditis before conventional measures of systolic dysfunction. Such developments mirror the aspirational goal of this review—shifting from static image interpretation toward dynamic, patient-specific decision support. As multimodal data integration expands, linking echocardiography with hemodynamic monitoring and genetic data may further enhance personalized intervention planning (L. Jiang et al., 2025).

Limitations and Future Directions

While the cumulative evidence underscores AI's transformative potential, methodological heterogeneity remains a barrier to meta-analytic synthesis. Differences in imaging hardware, annotation protocols, and evaluation metrics hinder direct comparison. Furthermore, few pediatric AI studies have undergone prospective, randomized clinical validation—a step necessary for regulatory approval and ethical implementation. Future research should prioritize multicenter, longitudinal studies employing harmonized evaluation frameworks and standardized performance benchmarks such as Dice similarity coefficients for segmentation and Bland–Altman analysis for agreement. Beyond accuracy metrics, investigators should assess downstream clinical outcomes, such as decision modification rates, diagnostic turnaround time, and cost-effectiveness. Integrating continuous learning systems that update models with new patient data under institutional oversight may represent the next phase of safe, adaptive AI in pediatric echocardiography.

CONCLUSION

In summary, this review confirms that AI-driven echocardiography represents a paradigm shift in pediatric critical cardiology. The technology has matured from pilot experimentation to clinically relevant, reproducible applications capable of augmenting diagnostic and therapeutic decisions. By refining acquisition, standardizing quantification, and offering real-time support, AI extends the reach of echocardiography into scenarios where expert sonographers are unavailable and time is of the essence. Nonetheless, realizing its full clinical potential requires overcoming data, ethical, and regulatory challenges through collaboration among engineers, clinicians, and ethicists. The path from images to interventions is thus not only technological but profoundly human—anchored in trust, transparency, and a shared commitment to improving pediatric cardiovascular care.

Acknowledgement: The authors extend their appreciation to the Arab Open University for funding this research work.

Funding Statement: This research was funded by the Arab Open University, Riyadh, Kingdom of Saudi Arabia.

REFERENCES

1. Agrawal, R., Gupta, T., Gupta, S., Chauhan, S., Patel, P., & Hamdare, S. (2025). Fostering trust and interpretability: integrating explainable AI (XAI) with machine learning for enhanced disease prediction and decision transparency. *Diagnostic Pathology*, *20*(1), 105. https://doi.org/10.1186/s13000-025-01686-3
2. AI in Echocardiography: State-of-the-art Automated Measurement Techniques and Clinical Applications. (2025). *JMA Journal*, *8*(1), 141–150. https://doi.org/10.31662/jmaj.2024-0180
3. Allam, A., Feuerriegel, S., Rebhan, M., & Krauthammer, M. (2021). Analyzing Patient Trajectories With Artificial Intelligence. *Journal of Medical Internet Research*, *23*(12), e29812. https://doi.org/10.2196/29812
4. Allen, J. W., Earp, B. D., & Wilkinson, D. (2025). AI-assisted consent in paediatric medicine: ethical implications of using large language models to support decision-making. *Journal of Medical Ethics*, jme-2024-110624. https://doi.org/10.1136/jme-2024-110624
5. Alsharqi, M., & Edelman, E. R. (2025). Artificial Intelligence in Cardiovascular Imaging and Interventional Cardiology: Emerging Trends and Clinical Implications. *Journal of the Society for Cardiovascular Angiography & Interventions*, *4*(3), 102558. https://doi.org/10.1016/j.jscai.2024.102558
6. Alvarez, J. A., Wilkinson, J. D., & Lipshultz, S. E. (2007). Outcome predictors for pediatric dilated cardiomyopathy: A systematic review. *Progress in Pediatric Cardiology*, *23*(1–2), 25–32. https://doi.org/10.1016/j.ppedcard.2007.05.009
7. Arnaout, R., Curran, L., Zhao, Y., Levine, J. C., Chinn, E., & Moon-Grady, A. J. (2021). An ensemble of neural networks provides expert-level prenatal detection of complex congenital heart disease. *Nature Medicine*, *27*(5), 882–891. https://doi.org/10.1038/s41591-021-01342-5
8. Bretthauer, M., & Kalager, M. (2018). When no guideline recommendation is the best recommendation. *The Lancet*, *392*(10151), 898–899. https://doi.org/10.1016/S0140-6736(18)31671-4
9. Brown, K., Roshanitabrizi, P., Rwebembera, J., Okello, E., Beaton, A., Linguraru, M. G., & Sable, C. A. (2024). Using Artificial Intelligence for Rheumatic Heart Disease Detection by Echocardiography: Focus on Mitral Regurgitation. *Journal of the American Heart Association*, *13*(2), 1–10. https://doi.org/10.1161/JAHA.123.031257
10. Chen, W., Wu, J., Zhang, Z., Gao, Z., Chen, X., Zhang, Y., Lin, Z., Tang, Z., Yu, W., Fan, S., Zhang, H., & Xia, B. (2024). Artificial intelligence-assisted echocardiographic monitoring in pediatric patients on extracorporeal membrane oxygenation. *Frontiers in Cardiovascular Medicine*, *11*(December), 1–11. https://doi.org/10.3389/fcvm.2024.1418741
11. Chilamkurthy, S., Ghosh, R., Tanamala, S., Biviji, M., Campeau, N. G., Venugopal, V. K., Mahajan, V., Rao, P., & Warier, P. (2018). Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. *The Lancet*, *392*(10162), 2388–2396. https://doi.org/10.1016/S0140-6736(18)31645-3
12. Chilcote, D., Sriram, A., Slovis, J., Morgan, R. W., Schaubel, D. E., Connelly, J., Berg, R. A., Keim, G., Yehya, N., Kilbaugh, T., & Himebauch, A. S. (2024). Venovenous Extracorporeal Membrane Oxygenation Initiation for Pediatric Acute Respiratory Distress Syndrome With Cardiovascular Instability is Associated With an Immediate and Sustained Decrease in Vasoactive-Inotropic Scores. *Pediatric Critical Care Medicine*, *25*(1), e41–e46. https://doi.org/10.1097/PCC.0000000000003325
13. Choudhury, A., & Urena, E. (2022). Artificial Intelligence in NICU and PICU: A Need for Ecological Validity, Accountability, and Human Factors. *Healthcare*, *10*(5), 952. https://doi.org/10.3390/healthcare10050952
14. Dellas, C., Kammerer, L., Gravenhorst, V., Lotz, J., Paul, T., & Steinmetz, M. (2018). Quantification of pulmonary regurgitation and prediction of pulmonary valve replacement by echocardiography in patients with congenital heart defects in comparison to cardiac magnetic resonance imaging. *International Journal of Cardiovascular Imaging*, *34*(4), 607–613. https://doi.org/10.1007/s10554-017-1267-z
15. Edpuganti, S., Shamim, A., Gangolli, V. H., Weerasekara, R. A. D. K. N. W., & Yellamilli, A. (2025). Artificial Intelligence in Cardiovascular Imaging: Current Landscape, Clinical Impact, and Future Directions. *Discoveries*, *13*(2), e211. https://doi.org/10.15190/d.2025.10
16. Edwards, L. A., Yang, C., Sharma, S., Chen, Z. H., Gorantla, L., Joshi, S. A., Longhi, N. J., Worku, N., Yang, J. S., Martinez Di Pietro, B., Armenian, S., Bhat, A., Border, W., Buddhe, S., Blythe, N., Stratton, K., Leger, K. J., Leisenring, W. M., Meacham, L. R., … Boyle, P. M. (2024). Building a machine learning-assisted echocardiography prediction tool for children at risk for cancer therapy-related cardiomyopathy. *Cardio-Oncology*, *10*(1). https://doi.org/10.1186/s40959-

024-00268-4
17. Ge, S. (2013). Pediatric Echocardiography: New Developments and Applications. *Echocardiography*, *30*(4), 426–427. https://doi.org/10.1111/echo.12210
18. Gearhart, A., Goto, S., Deo, R. C., & Powell, A. J. (2022). An Automated View Classification Model for Pediatric Echocardiography Using Artificial Intelligence. *Journal of the American Society of Echocardiography*, *35*(12), 1238–1246. https://doi.org/10.1016/j.echo.2022.08.009
19. Grotberg, J. C., McDonald, R. K., & Co, I. N. (2024). Point-of-Care Echocardiography in the Difficult-to-Image Patient in the ICU: A Narrative Review. *Critical Care Explorations*, *6*(1), e1035. https://doi.org/10.1097/CCE.0000000000001035
20. Guo, L., Lei, B., Chen, W., Du, J., Frangi, A. F., Qin, J., Zhao, C., Shi, P., Xia, B., & Wang, T. (2021). Dual attention enhancement feature fusion network for segmentation and quantitative analysis of paediatric echocardiography. *Medical Image Analysis*, *71*, 102042. https://doi.org/10.1016/j.media.2021.102042
21. Higgins, O., & Wilson, R. L. (2025). Integrating Artificial Intelligence (<scp>AI</scp>) With Workforce Solutions for Sustainable Care: A Follow Up to Artificial Intelligence and Machine Learning (<scp>ML</scp>) Based Decision Support Systems in Mental Health. *International Journal of Mental Health Nursing*, *34*(2). https://doi.org/10.1111/inm.70019
22. Hu, Y., Guo, L., Lei, B., Mao, M., Jin, Z., Elazab, A., Xia, B., & Wang, T. (2019). Fully Automatic Pediatric Echocardiography Segmentation Using Deep Convolutional Networks Based on BiSeNet. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 6561–6564. https://doi.org/10.1109/EMBC.2019.8856457
23. Jiang, L., Zuo, H. J., & Chen, C. (2025). Artificial intelligence in echocardiography: Applications and future directions. *Fundamental Research*. https://doi.org/10.1016/j.fmre.2025.01.020
24. Jiang, X., Yu, J., Ye, J., Jia, W., Xu, W., & Shu, Q. (2023). A deep learning-based method for pediatric congenital heart disease detection with seven standard views in echocardiography. *World Journal of Pediatric Surgery*, *6*(3), 1–8. https://doi.org/10.1136/wjps-2023-000580
25. Li, L., Homer, P., Craft, M., Kutty, S., Putschoegl, A., Marshall, A., Danford, D., & Yetman, A. (2024). Machine Learning-Enabled Fully Automated Assessment of Left Ventricular Volume, Ejection Fraction and Strain: Experience in Pediatric and Young Adult Echocardiography. *Pediatric Cardiology*, *45*(6), 1183–1191. https://doi.org/10.1007/s00246-022-03015-7
26. Lin, X., Yang, F., Chen, Y., Chen, X., Wang, W., Li, W., Wang, Q., Zhang, L., Li, X., Deng, Y., Pu, H., Chen, X., Wang, X., Luo, D., Zhang, P., Burkhoff, D., & He, K. (2023). Echocardiography-based AI for detection and quantification of atrial septal defect. *Frontiers in Cardiovascular Medicine*, *10*(March), 1–10. https://doi.org/10.3389/fcvm.2023.985657
27. Lipshultz, S. E., Law, Y. M., Asante-Korang, A., Austin, E. D., Dipchand, A. I., Everitt, M. D., Hsu, D. T., Lin, K. Y., Price, J. F., Wilkinson, J. D., & Colan, S. D. (2019). Cardiomyopathy in Children: Classification and Diagnosis: A Scientific Statement From the American Heart Association. *Circulation*, *140*(1). https://doi.org/10.1161/CIR.0000000000000682
28. Liu, X., Fan, Y., Li, S., Chen, M., Li, M., Hau, W. K., Zhang, H., Xu, L., & Lee, A. P. W. (2021). Deep learning-based automated left ventricular ejection fraction assessment using 2-D echocardiography. *American Journal of Physiology - Heart and Circulatory Physiology*, *321*(2), H390–H399. https://doi.org/10.1152/ajpheart.00416.2020
29. Lopez, L., Saurers, D. L., Barker, P. C. A., Cohen, M. S., Colan, S. D., Dwyer, J., Forsha, D., Friedberg, M. K., Lai, W. W., Printz, B. F., Sachdeva, R., Soni-Patel, N. R., Truong, D. T., Young, L. T., & Altman, C. A. (2024). Guidelines for Performing a Comprehensive Pediatric Transthoracic Echocardiogram: Recommendations From the American Society of Echocardiography. *Journal of the American Society of Echocardiography*, *37*(2), 119–170. https://doi.org/10.1016/j.echo.2023.11.015
30. Madani, A., Arnaout, R., Mofrad, M., & Arnaout, R. (2018). Fast and accurate view classification of echocardiograms using deep learning. *Npj Digital Medicine*, *1*(1), 6. https://doi.org/10.1038/s41746-017-0013-1
31. Maturi, B., Dulal, S., Sayana, S. B., Ibrahim, A., Ramakrishna, M., Chinta, V., Sharma, A., & Ravipati, H. (2025). Revolutionizing Cardiology: The Role of Artificial Intelligence in Echocardiography. *Journal of Clinical Medicine*, *14*(2), 625. https://doi.org/10.3390/jcm14020625
32. Meng, X., Song, M., Zhang, K., Lu, W., Li, Y., Zhang, C., & Zhang, Y. (2024). Congenital heart disease: types, pathophysiology, diagnosis, and treatment options. *MedComm*, *5*(7). https://doi.org/10.1002/mco2.631
33. Meza, J. M., Slieker, M., Blackstone, E. H., Mertens, L., DeCampli, W. M., Kirklin, J. K., Karimi, M., Eghtesady, P., Pourmoghadam, K., Kim, R. W., Burch, P. T., Jacobs, M. L., Karamlou, T., & McCrindle, B. W. (2018). A novel, data-driven conceptualization for critical left heart obstruction. *Computer Methods and Programs in Biomedicine*, *165*, 107–116. https://doi.org/10.1016/j.cmpb.2018.08.014
34. Myhre, P. L., Grenne, B., Asch, F. M., Delgado, V., Khera, R., Lafitte, S., Lang, R. M., Pellikka, P. A., Sengupta, P. P., Vemulapalli, S., & Lam, C. S. P. (2025). Artificial intelligence-enhanced echocardiography in cardiovascular disease management. *Nature Reviews Cardiology*. https://doi.org/10.1038/s41569-025-01197-0
35. Narang, A., Bae, R., Hong, H., Thomas, Y., Surette, S., Cadieu, C., Chaudhry, A., Martin, R. P., McCarthy, P. M., Rubenson, D. S., Goldstein, S., Little, S. H., Lang, R. M., Weissman, N. J., & Thomas, J. D. (2021). Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use. *JAMA Cardiology*, *6*(6), 624–632. https://doi.org/10.1001/jamacardio.2021.0185
36. Narula, S., Shameer, K., Salem Omar, A. M., Dudley, J. T., & Sengupta, P. P. (2016). Machine-Learning Algorithms to Automate Morphological and Functional Assessments in 2D Echocardiography. *Journal of the American College of Cardiology*, *68*(21), 2287–2295. https://doi.org/10.1016/j.jacc.2016.08.062

37. Nguyen, M. B., Villemain, O., Friedberg, M. K., Lovstakken, L., Rusin, C. G., & Mertens, L. (2022). Artificial intelligence in the pediatric echocardiography laboratory: Automation, physiology, and outcomes. *Frontiers in Radiology*, *2*(Dl). https://doi.org/10.3389/fradi.2022.881777
38. Obuchowicz, R., Lasek, J., Wodziński, M., Piórkowski, A., Strzelecki, M., & Nurzynska, K. (2025). Artificial Intelligence-Empowered Radiology—Current Status and Critical Review. *Diagnostics*, *15*(3), 282. https://doi.org/10.3390/diagnostics15030282
39. Olaisen, S., Smistad, E., Espeland, T., Hu, J., Pasdeloup, D., Østvik, A., Aakhus, S., Rösner, A., Malm, S., Stylidis, M., Holte, E., Grenne, B., Løvstakken, L., & Dalen, H. (2024). Automatic measurements of left ventricular volumes and ejection fraction by artificial intelligence: clinical validation in real time and large databases. *European Heart Journal - Cardiovascular Imaging*, *25*(3), 383–395. https://doi.org/10.1093/ehjci/jead280
40. Ouyang, D., He, B., Ghorbani, A., Yuan, N., Ebinger, J., Langlotz, C. P., Heidenreich, P. A., Harrington, R. A., Liang, D. H., Ashley, E. A., & Zou, J. Y. (2020). Video-based AI for beat-to-beat assessment of cardiac function. *Nature*, *580*(7802), 252–256. https://doi.org/10.1038/s41586-020-2145-8
41. Park, T., Lee, I.-H., Lee, S. W., & Kong, S. W. (2025). Artificial intelligence in pediatric healthcare: current applications, potential, and implementation considerations. *Clinical and Experimental Pediatrics*, *68*(9), 641–651. https://doi.org/10.3345/cep.2025.00962
42. Peck, D., Rwebembera, J., Nakagaayi, D., Minja, N. W., Ollberding, N. J., Pulle, J., Klein, J., Adams, D., Martin, R., Koepsell, K., Sanyahumbi, A., Beaton, A., Okello, E., & Sable, C. (2023). The Use of Artificial Intelligence Guidance for Rheumatic Heart Disease Screening by Novices. *Journal of the American Society of Echocardiography*, *36*(7), 724–732. https://doi.org/10.1016/j.echo.2023.03.001
43. Rabbani, S. A., El-Tanani, M., Sharma, S., Rabbani, S. S., El-Tanani, Y., Kumar, R., & Saini, M. (2025). Generative Artificial Intelligence in Healthcare: Applications, Implementation Challenges, and Future Directions. *BioMedInformatics*, *5*(3), 37. https://doi.org/10.3390/biomedinformatics5030037
44. Reddy, C. D., Lopez, L., Ouyang, D., Zou, J. Y., & He, B. (2023). Video-Based Deep Learning for Automated Assessment of Left Ventricular Ejection Fraction in Pediatric Patients. *Journal of the American Society of Echocardiography*, *36*(5), 482–489. https://doi.org/10.1016/j.echo.2023.01.015
45. Salybekov, A. A., Wolfien, M., Hahn, W., Hidaka, S., & Kobayashi, S. (2024). Artificial Intelligence Reporting Guidelines' Adherence in Nephrology for Improved Research and Clinical Outcomes. *Biomedicines*, *12*(3), 606. https://doi.org/10.3390/biomedicines12030606
46. Shamszare, H., & Choudhury, A. (2023). Clinicians' Perceptions of Artificial Intelligence: Focus on Workload, Risk, Trust, Clinical Decision Making, and Clinical Integration. *Healthcare*, *11*(16), 2308. https://doi.org/10.3390/healthcare11162308
47. Shokr, A. A.-E. S., Tomerak, R. H., Agha, H. M., ElKaffas, R. M. H., & Ali, S. B. I. (2023). Echocardiography-directed management of hemodynamically unstable neonates in tertiary care hospitals. *Egyptian Pediatric Association Gazette*, *71*(1), 10. https://doi.org/10.1186/s43054-023-00157-y
48. Singh, M. P., & Keche, Y. N. (2025). Ethical Integration of Artificial Intelligence in Healthcare: Narrative Review of Global Challenges and Strategic Solutions. *Cureus*. https://doi.org/10.7759/cureus.84804
49. Singh, Y. (2017). Echocardiographic Evaluation of Hemodynamics in Neonates and Children. *Frontiers in Pediatrics*, *5*. https://doi.org/10.3389/fped.2017.00201
50. Sullivan, B. A., Beam, K., Vesoulis, Z. A., Aziz, K. B., Husain, A. N., Knake, L. A., Moreira, A. G., Hooven, T. A., Weiss, E. M., Carr, N. R., El-Ferzli, G. T., Patel, R. M., Simek, K. A., Hernandez, A. J., Barry, J. S., & McAdams, R. M. (2024). Transforming neonatal care with artificial intelligence: challenges, ethical consideration, and opportunities. *Journal of Perinatology*, *44*(1), 1–11. https://doi.org/10.1038/s41372-023-01848-5
51. Sveric, K. M., Ulbrich, S., Dindane, Z., Winkler, A., Botan, R., Mierke, J., Trausch, A., Heidrich, F., & Linke, A. (2024). Improved assessment of left ventricular ejection fraction using artificial intelligence in echocardiography: A comparative analysis with cardiac magnetic resonance imaging. *International Journal of Cardiology*, *394*, 131383. https://doi.org/10.1016/j.ijcard.2023.131383
52. Tasmurzayev, N., Amangeldy, B., Imanbek, B., Baigarayeva, Z., Imankulov, T., Dikhanbayeva, G., Amangeldi, I., & Sharipova, S. (2025). Digital Cardiovascular Twins, AI Agents, and Sensor Data: A Narrative Review from System Architecture to Proactive Heart Health. *Sensors*, *25*(17), 5272. https://doi.org/10.3390/s25175272
53. Thompson, A. J., O'Leary, P. W., Miller, A., Martineau, S., Reece, C., Breuer, A., Eidem, B. W., Qureshi, M. Y., Nelson, T. J., Haile, D. T., Miller, K. S., Riess, L. A., Cavanaugh, K. M., & Timmons, L. (2021). Inter-observer and Inter-vendor Variability in Strain Measurements in Patients with Single Right Ventricular Anatomy. *Pediatric Cardiology*, *42*(6), 1341–1349. https://doi.org/10.1007/s00246-021-02617-x
54. Tolu-Akinnawo, O. Z., Ezekwueme, F., Omolayo, O., Batheja, S., & Awoyemi, T. (2025). Advancements in Artificial Intelligence in Noninvasive Cardiac Imaging: A Comprehensive Review. *Clinical Cardiology*, *48*(1). https://doi.org/10.1002/clc.70087
55. Tong, C., Du, X., Chen, Y., Zhang, K., Shan, M., Shen, Z., Zhang, H., & Zheng, J. (2024). Machine learning prediction model of major adverse outcomes after pediatric congenital heart surgery: a retrospective cohort study. *International Journal of Surgery*, *110*(4), 2207–2216. https://doi.org/10.1097/JS9.0000000000001112
56. Trujillo Rivera, E. A., Chamberlain, J. M., Patel, A. K., Zeng-Treitler, Q., Bost, J. E., Heneghan, J. A., Morizono, H., & Pollack, M. M. (2021). Predicting Future Care Requirements Using Machine Learning for Pediatric Intensive and Routine Care Inpatients. *Critical Care Explorations*, *3*(8), e0505. https://doi.org/10.1097/CCE.0000000000000505
57. Ufkes, S., Zuercher, M., Erdman, L., Slorach, C., Mertens, L., & Taylor, K. L. (2023). Automatic Prediction of Paediatric Cardiac Output From Echocardiograms Using Deep Learning Models. *CJC Pediatric and Congenital Heart Disease*, *2*(1), 12–19. https://doi.org/10.1016/j.cjcpc.2022.11.001

58. Vasile, C. M., Bouteiller, X. P., Avesani, M., Velly, C., Chan, C., Jalal, Z., Thambo, J. B., & Iriart, X. (2023). Exploring the Potential of Artificial Intelligence in Pediatric Echocardiography—Preliminary Results from the First Pediatric Study Using AI Software Developed for Adults. *Journal of Clinical Medicine*, *12*(9). https://doi.org/10.3390/jcm12093209
59. Wang, A., Doan, T. T., Reddy, C., & Jone, P. N. (2025). Artificial Intelligence in Fetal and Pediatric Echocardiography. *Children*, *12*(1), 1–18. https://doi.org/10.3390/children12010014
60. Wang, J., Liu, X., Wang, F., Zheng, L., Gao, F., Zhang, H., Zhang, X., Xie, W., & Wang, B. (2021). Automated interpretation of congenital heart disease from multi-view echocardiograms. *Medical Image Analysis*, *69*, 101942. https://doi.org/10.1016/j.media.2020.101942
61. Weiner, E. B., Dankwa-Mullan, I., Nelson, W. A., & Hassanpour, S. (2025). Ethical challenges and evolving strategies in the integration of artificial intelligence into clinical practice. *PLOS Digital Health*, *4*(4), e0000810. https://doi.org/10.1371/journal.pdig.0000810
62. Wu, L., Dong, B., Liu, X., Hong, W., Chen, L., Gao, K., Sheng, Q., Yu, Y., Zhao, L., & Zhang, Y. (2022). Standard Echocardiographic View Recognition in Diagnosis of Congenital Heart Defects in Children Using Deep Learning Based on Knowledge Distillation. *Frontiers in Pediatrics*, *9*(January), 1–11. https://doi.org/10.3389/fped.2021.770182
63. Xu, J., Li, Q., Deng, L., Xiong, J., Cheng, Z., & Ye, C. (2025). Global, regional, and national epidemiology of congenital heart disease in children from 1990 to 2021. *Frontiers in Cardiovascular Medicine*, *12*. https://doi.org/10.3389/fcvm.2025.1522644
64. Ye, Z., Chen, T., Wang, F., Zhang, H., & Zhang, L. (2025). Marrying Perona Malik diffusion with Mamba for efficient pediatric echocardiographic left ventricular segmentation. *Scientific Reports*, *15*(1), 1–12. https://doi.org/10.1038/s41598-025-16797-6
65. Yousefpour Shahrivar, R., Karami, F., & Karami, E. (2023). Enhancing Fetal Anomaly Detection in Ultrasonography Images: A Review of Machine Learning-Based Approaches. *Biomimetics*, *8*(7), 519. https://doi.org/10.3390/biomimetics8070519
66. Zhang, J., Gajjala, S., Agrawal, P., Tison, G. H., Hallock, L. A., Beussink-Nelson, L., Lassen, M. H., Fan, E., Aras, M. A., Jordan, C. R., Fleischmann, K. E., Melisko, M., Qasim, A., Shah, S. J., Bajcsy, R., & Deo, R. C. (2018). Fully automated echocardiogram interpretation in clinical practice: Feasibility and diagnostic accuracy. *Circulation*, *138*(16), 1623–1635. https://doi.org/10.1161/CIRCULATIONAHA.118.034338
67. Zuercher, M., Ufkes, S., Erdman, L., Slorach, C., Mertens, L., & Taylor, K. (2022). Retraining an Artificial Intelligence Algorithm to Calculate Left Ventricular Ejection Fraction in Pediatrics. *Journal of Cardiothoracic and Vascular Anesthesia*, *36*(9), 3610–3616. https://doi.org/10.1053/j.jvca.2022.05.004
68. Zürn, C., Hübner, D., Ziesenitz, V. C., Höhn, R., Schuler, L., Schlange, T., Gorenflo, M., Kari, F. A., Kroll, J., Loukanov, T., Klemm, R., & Stiller, B. (2023). Model-driven survival prediction after congenital heart surgery. *Interdisciplinary CardioVascular and Thoracic Surgery*, *37*(3). https://doi.org/10.1093/icvts/ivad089