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ARTIFICIAL INTELLIGENCE IN PEDIATRIC ELECTROCARDIOGRAPHY: DIAGNOSTIC APPLICATIONS, PREDICTIVE POTENTIAL, AND CLINICAL LIMITATIONS - A LITERATURE REVIEW

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ABSTRACT

Introduction Electrocardiography (ECG) remains a fundamental diagnostic tool in pediatric cardiology; however, its interpretation is challenging because normal electrocardiographic parameters vary considerably with age and cardiovascular maturation. The development of artificial intelligence (AI), particularly machine learning and deep learning, has created new possibilities for automated ECG analysis and the detection of subtle patterns that may be difficult to identify using conventional interpretation. This review aims to summarize current applications of AI in pediatric electrocardiography, with particular emphasis on diagnostic and predictive applications and their clinical potential.

Current State of Knowledge Current evidence indicates that AI-based models can support the automated interpretation of pediatric ECGs and the detection of rhythm and conduction disorders, including Wolff-Parkinson-White syndrome, long QT syndrome, and congenital heart disease. Deep learning models have also demonstrated the ability to estimate corrected QT intervals and to identify ECG patterns associated with left ventricular dysfunction, hypertrophy, and dilation. Beyond conventional diagnosis, AI-ECG has shown potential for prognostic applications, including the prediction of adverse cardiovascular events in children. These findings suggest that AI models can extract complex information from ECG recordings beyond individual conventional parameters. However, the available evidence remains limited by relatively small and heterogeneous pediatric datasets, age-related variability in ECG characteristics, data heterogeneity, limited external validation, and the predominance of retrospective studies. Moreover, evidence regarding the impact of AI-ECG on clinical decision-making and patient outcomes remains limited.

Conclusions AI represents a promising approach to expanding the diagnostic and prognostic potential of pediatric electrocardiography. Current findings support its role as a tool for automated ECG interpretation, disease detection, risk stratification, and indirect assessment of cardiac structure and function. Nevertheless, AI-ECG should currently be regarded as a clinical decision-support tool rather than a replacement for conventional cardiac assessment. Further multicenter, prospective, and externally validated studies are needed to establish the generalizability, safety, interpretability, and clinical utility of AI-based ECG models in pediatric practice.

KEYWORDS

Pediatric Electrocardiography, Artificial Intelligence, Cardiovascular Diagnostics, ECG Interpretation, Clinical Decision Support, Deep Learning

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Introduction and Objective

Electrocardiography (ECG) remains one of the fundamental, widely available, and non-invasive diagnostic tools used in pediatric cardiology. In clinical practice, ECG is used, among other purposes, for the diagnosis of rhythm and conduction disorders, congenital heart defects, cardiomyopathies, and diseases associated with abnormalities of cardiac repolarization. At the same time, interpretation of the electrocardiographic recording in children is particularly challenging because normal values for many ECG parameters change with age and maturation of the cardiovascular system. [1,2]

The development of artificial intelligence (AI) methods has created new opportunities for the automated analysis of electrocardiographic signals. Unlike conventional algorithms based on predefined signal features, AI models can identify complex and potentially imperceptible patterns directly within ECG data. Advances in this field enable not only the automated classification of abnormal signals, but also the detection of specific disease entities, risk assessment, and prediction of future clinical events. [2,3] The potential of AI-ECG extends beyond conventional diagnostics. Increasing attention is being given to the use of the electrocardiogram as a source of prognostic information. This approach may expand the role of electrocardiography from a tool primarily used to identify existing abnormalities to a tool that can also support early risk stratification. [4–6]

Despite promising results, the application of AI in pediatric electrocardiography remains an area requiring further investigation. The current literature highlights several challenges, including limited sample

sizes in some populations, a predominance of retrospective studies, the use of data from single centers, and age-related variability in normal ECG parameters. [2]

The aim of this review is to present current applications of artificial intelligence in the analysis of pediatric electrocardiograms, with particular emphasis on diagnostic and predictive applications, assessment of model performance, and identification of limitations that may hinder their implementation in clinical practice.

Materials and Methods

This study was prepared as a non-systematic literature review concerning the application of artificial intelligence (AI) in the analysis of electrocardiograms (ECG) in children and adolescents. The aim of the literature search was to identify current studies addressing both diagnostic and predictive applications of AI models based on electrocardiographic data, as well as to assess their performance, potential clinical applicability, and major limitations.

The literature search was conducted using the PubMed, Scopus, and Web of Science databases, while Google Scholar was used as a supplementary source to identify additional publications. The search strategy included publications published between 2015 and 2026, with particular emphasis on studies published between 2020 and 2026. The search was performed using combinations of keywords related to artificial intelligence, electrocardiography, and the pediatric population. The search terms included, among others: “artificial intelligence,” “machine learning,” “deep learning,” “neural network,” “convolutional neural network,” “electrocardiography,” and “pediatric.”

Publications were included if they met the following criteria: they involved a pediatric population, including neonates, infants, children, or adolescents up to 18 years of age; used ECG recordings as input data for an AI model; evaluated the application of the model for diagnosis, detection of specific disease phenotypes, risk stratification, or prediction of clinical events; and reported results regarding model performance or its potential clinical applicability. Publications involving exclusively adult populations, studies not directly related to ECG analysis, and non-research reports were excluded. Studies involving both pediatric and adult populations were included when pediatric results were reported separately or when the study was considered particularly relevant to the review topic.

A limitation of this review is its non-systematic nature, which entails the possibility of publication selection bias and the absence of a formal meta-analysis. In addition, substantial methodological heterogeneity among the analyzed studies, including differences in populations, AI algorithms, and validation methods, limits the possibility of directly comparing the reported results.

Current State of Knowledge

AI in Automated Interpretation of Pediatric ECG

One of the fundamental and rapidly developing applications of artificial intelligence in pediatric electrocardiography is the automated interpretation of ECG recordings. Traditional computerized electrocardiographic analysis systems primarily rely on measurements of predefined parameters, such as heart rate, time intervals, wave amplitudes, and conduction characteristics. The development of machine learning (ML), particularly deep learning (DL), has enabled a shift away from this approach. ML models can learn relationships between ECG features and specific diagnoses from large datasets, whereas DL models, including convolutional neural networks (CNNs), can analyze multidimensional representations of the signal and automatically identify features relevant to classification. In ECG analysis, this enables the use of not only individual parameters but also relationships between leads, waveform morphology, temporal intervals, and subtle changes across the entire recording. [2,7]

An important advantage of deep learning is that it reduces the need for manual feature engineering. In conventional systems, it is necessary to determine which parameters should be measured and how they should be interpreted. In contrast, a DL model can automatically extract signal representations during the training process. In practice, this enables the analysis of very large numbers of ECG recordings and may facilitate the detection of patterns that are not readily apparent during standard electrocardiographic interpretation. [2,7] One potential application of AI is the automated differentiation between normal and abnormal ECG recordings. More advanced models can perform multiclass classification, enabling the identification of specific abnormalities or disease entities. In this context, AI-ECG may serve as a screening tool by identifying

recordings requiring further evaluation and may also assist clinicians in interpreting cases in which abnormalities are subtle or difficult to recognize based on individual parameters alone. [2]

A particularly important contribution to the development of pediatric AI-ECG was made by Mayourian et al. in a study published in 2025, which evaluated the performance of a deep neural network for the automated interpretation of 12-lead ECG recordings. The analysis included 201,620 patients and 583,134 electrocardiographic recordings, with a median patient age of 11.7 years. The model was designed to detect both general ECG abnormalities and selected diagnoses, including Wolff-Parkinson-White (WPW) syndrome and prolonged QTc intervals. In comparative analyses, the model outperformed commercially available software used for automated ECG interpretation. These findings indicate that deep learning models can achieve high performance in the automated classification of pediatric ECG recordings and may represent a valuable tool for supporting clinical interpretation. [3]

The application of AI in pediatric electrocardiography is particularly relevant because the characteristics of a normal ECG change with age. Heart rate, electrical axis, conduction intervals, wave amplitudes, and repolarization characteristics vary throughout development. Therefore, models designed for pediatric populations should account for the broad range of physiological age-related variability. [2]

AI in the Diagnosis of Rhythm and Conduction Disorders

Rhythm and conduction disorders constitute an important group of abnormalities evaluated by electrocardiography in children. One of the most advanced applications of AI in this field is the diagnosis of pre-excitation and Wolff-Parkinson-White (WPW) syndrome. On a conventional ECG, the presence of an accessory pathway may be suggested by a shortened PR interval, the presence of a delta wave, and widening of the QRS complex. However, accurately localizing the accessory pathway remains a particular challenge, as this information is important for planning catheter ablation. Conventional localization algorithms based on specific characteristics of the delta wave and QRS complex have demonstrated limited accuracy, particularly in pediatric populations. [8]

Henneken et al. developed a multi-task deep learning model for localizing accessory pathways in patients with WPW syndrome. The model was evaluated using 1,394 ECG recordings from 567 patients and subsequently assessed in two independent test datasets. The resulting AUROC for accessory pathway localization was 0.92, compared with 0.80 and 0.81 for the conventional Arruda and Milstein algorithms, respectively. [9] These findings suggest that analysis of the entire ECG signal using a neural network may enable the use of information that is more difficult to capture with conventional rule-based approaches.

Another interesting application of AI is the detection of concealed accessory pathways. When an accessory pathway conducts exclusively in the retrograde direction, a standard sinus-rhythm ECG may not show typical features of pre-excitation. Wang et al. used convolutional neural network models to analyze ECG recordings from patients with concealed accessory pathways. In the test dataset, several analyses achieved sensitivity above 87% and specificity above 98%, despite the absence of significant differences in basic ECG parameters between patients with concealed accessory pathways and controls. [10]

AI can also be used for more general classification of rhythm and conduction disorders. Deep learning models can analyze the morphology of consecutive P-QRS-T complexes, the intervals between them, and relationships between individual ECG leads. However, current pediatric evidence remains substantially less extensive than the literature in adults, and many models have been developed using relatively small or highly selected datasets. [2,11]

The detection of rare rhythm disorders also remains a significant challenge. The small number of cases representing individual arrhythmias in training datasets may lead to class imbalance and limit the ability to correctly identify rare phenotypes. In addition, a single 12-lead ECG recording captures only a brief period of the heart's electrical activity and therefore may not always detect paroxysmal rhythm disorders. Consequently, future applications of AI in pediatric electrophysiology may require the integration of data from routine ECG recordings, long-term monitoring, and other sources of clinical information. [2,11]

AI in the Diagnosis of Long QT Syndrome

Long QT syndrome (LQTS) is an inherited disorder of cardiac electrical activity characterized by prolonged ventricular repolarization and an increased risk of life-threatening ventricular arrhythmias. The application of artificial intelligence offers an opportunity to move beyond the analysis of individual parameters and exploit information contained in the entire 12-lead ECG recording. Deep learning models can identify relationships between T-wave morphology, the QRS complex, temporal intervals, and information derived from different ECG leads. This approach may enable the detection of subtle features associated with LQTS that are not always apparent during standard electrocardiographic assessment. [12]

One study demonstrating this application was conducted by Aufiero et al. [6] The authors analyzed 12-lead ECG recordings from patients with congenital LQTS and individuals without the diagnosis. A one-dimensional convolutional neural network (1D-CNN) was used, receiving the ECG signal directly as input and learning to distinguish between patient groups. Thus, the model was not programmed by the researchers using predefined features such as QT duration or T-wave amplitude, but instead learned to identify patterns present in the ECG recordings. The model achieved high performance in distinguishing individual LQTS subtypes, with AUC values of approximately 0.90–0.92. Particularly noteworthy was the use of explainable AI methods to determine which parts of the ECG influenced the model's decisions. The analysis showed that the algorithm focused not only on the QT interval itself but also on other components of the recording, including regions around the onset of the QRS complex. [6] AI may therefore exploit combinations of ECG features whose significance is not incorporated into standard LQTS assessment. However, this does not mean that each of these features represents an independent marker of the disease.

Another research direction involves the use of AI to differentiate genetic LQTS subtypes. Jiang et al. [12] developed a deep learning model designed first to detect LQTS from the ECG and subsequently to predict its genetic subtype. The study included 4,521 ECG recordings from 990 patients. The model was also evaluated in an independent external population. In external validation, the model achieved an AUC of 0.93 for LQTS detection and 0.91 for differentiation of genetic subtypes. The significance of this study lies in demonstrating that ECG recordings may contain information that enables not only identification of the LQTS phenotype but also inference regarding its genetic basis. [12]

Ruiz et al. developed the pedQTNet model specifically for the pediatric population. [7] In this case, the objective was not to identify a specific genetic LQTS subtype but rather to automatically estimate the corrected QT interval (QTc) from a multi-lead ECG recording. The model was developed using 65,370 ECG recordings from 37,992 patients aged 0–18 years. Training was based on QTc measurements performed by pediatric electrophysiology specialists, allowing the model to learn to replicate their approach to ECG assessment. The authors then evaluated whether pedQTNet could identify children with prolonged QTc. At a QTc threshold of 470 ms, the model achieved a sensitivity of 85% and specificity of 87%. [7]

AI may therefore be used not only for the “diagnosis of LQTS,” but also for the more fundamental yet clinically important task of standardizing and automating QTc measurement in children. This is particularly relevant given the challenges associated with manual QT measurement and the variability of ECG parameters across different age groups. However, the model does not replace the overall diagnostic process for LQTS, as diagnosis also requires consideration of symptoms, family history, genetic testing results, and other clinical information.

AI in the Diagnosis of Congenital Heart Disease

Congenital heart disease (CHD) represents another group of conditions in which electrocardiography can provide information that may be exploited by artificial intelligence models. Conventional ECG does not directly visualize anatomical abnormalities; however, congenital heart defects may produce characteristic changes in the electrical axis, conduction, cardiac chamber hypertrophy, and repolarization.

One important study in this field was conducted by Chen et al. [13], who developed a model for detecting congenital heart disease from 12-lead ECG recordings in children. An important aspect of the study was the integration of deep learning with clinical information related to disease phenotype. The authors used an approach referred to as the incorporation of “human concepts,” whereby the model was not limited to direct classification of the ECG recording but also incorporated indirect features associated with the clinical manifestation of the defect. The model was subsequently compared with ECG assessments performed by cardiologists. It was developed using 65,869 cases and evaluated on an independent dataset of 12,000 cases. For CHD detection, the model achieved an AUC of 0.915 and a specificity of 0.881. [13] These findings

indicate the potential use of AI as a screening tool to support the identification of children who may require further diagnostic evaluation.

An interesting example of AI applied to the detection of a specific congenital defect is congenitally corrected transposition of the great arteries (ccTGA). This is a rare condition whose diagnosis may be delayed because of its complex anatomy and variable clinical presentation. Ghelani et al. [16] developed a convolutional neural network model that analyzed ECG recordings to identify patients with ccTGA. The study included 61,482 patients, of whom 0.7% had a diagnosis of ccTGA. Using saliency maps, the authors examined which portions of the ECG signal contributed most strongly to the model's decision. The most important features included QRS widening, negative QRS complexes in leads V1–V2, and the absence of Q waves in the lateral precordial leads. The model achieved an AUROC of 0.95, indicating a high ability to distinguish patients with ccTGA from those without the condition. [16]

A common feature of these studies is the use of ECG as an indirect source of information about cardiac structure and function. The algorithm does not directly “see” the anatomical defect but instead identifies electrophysiological patterns associated with its presence.

AI-ECG in the Prediction of Left Ventricular Dysfunction

One of the most important studies in this area was conducted by Mayourian et al. [3] The authors developed a deep learning model using 12-lead ECG recordings paired with corresponding echocardiographic data. The training dataset included 92,377 ECG–echocardiography pairs from a pediatric population. The model was designed to identify three major left ventricular abnormalities: systolic dysfunction, left ventricular hypertrophy, and left ventricular dilation. For left ventricular systolic dysfunction, the model achieved an AUROC of approximately 0.94, while the AUROC was approximately 0.87 for left ventricular dilation and 0.84 for left ventricular hypertrophy. [17] These findings indicate that information contained in routine ECG recordings can be used by a neural network to identify children with abnormalities that are conventionally detected by echocardiography.

The authors also analyzed which ECG features influenced the model's decisions. Saliency map analysis showed that precordial QRS complexes were particularly important across all evaluated outcomes. For left ventricular dysfunction, the model additionally focused on T waves, with T-wave inversion in the lateral leads representing one of the relevant patterns. In the prediction of left ventricular hypertrophy, important features included deep S waves in V1–V2 and tall R waves in V5–V6, whereas tall R waves in V4–V6 were particularly relevant for the prediction of left ventricular dilation. [3]

Subsequent studies extended this approach to children with congenital heart disease. In this population, ventricular dysfunction may result from the underlying anatomy of the defect, previous cardiac surgery, or chronic volume or pressure overload. AI-ECG models may therefore potentially use electrical activity as an indirect marker of functional changes occurring in the heart. In a multicenter study, Mayourian et al. evaluated the ability to predict left ventricular systolic dysfunction and remodeling in patients with congenital heart disease. In external validation, the model achieved an AUROC of approximately 0.89 for left ventricular systolic dysfunction and 0.83 for left ventricular dilation. [6] These findings demonstrate that AI may use ECG not only to identify specific electrocardiographic patterns but also to infer structural and functional characteristics of the heart indirectly.

AI-ECG in the Prediction of Cardiovascular Events

Another direction in the development of artificial intelligence in electrocardiography is the use of ECG recordings not only to identify existing abnormalities but also to assess the risk of future cardiovascular events. One study directly evaluating the potential of AI-ECG to predict adverse cardiovascular events in children was conducted by Nogimori et al. [17] The authors analyzed 21,378 ECG recordings from 8,324 children. Based on these data, they developed a convolutional neural network designed to generate an index referred to as the electrical heart failure indicator (EHFI). The model utilized ECG recordings together with information related to the concentration of B-type natriuretic peptide (BNP), a biomarker of cardiac overload and heart failure. The authors then assessed whether the EHFI value derived from the ECG could predict the occurrence of major adverse cardiovascular events (MACE).

In the prognostic analysis, which included 813 ECG recordings from 295 children, EHFI achieved an AUC of 0.826 for predicting MACE within 180 days, compared with an AUC of 0.691 for BNP; the difference was statistically significant ($p = 0.03$). Higher EHFI values were also associated with an increased risk of cardiovascular events (HR 16.5 for log-transformed EHFI). [17]

Limitations of the Current State of Knowledge

Despite promising research findings, the application of artificial intelligence in pediatric electrocardiography remains limited by several factors. One of the most important is the limited availability of large, representative pediatric datasets. Many models have been developed using data from single centers or selected populations, which may limit their applicability to other patient groups. This issue is particularly relevant for rare diseases, for which the number of available ECG recordings is often small.

Another limitation is the substantial age-related heterogeneity within the pediatric population. Normal ECG characteristics change from infancy through adolescence; therefore, models should account for the physiological dependence of electrocardiographic parameters on age. An algorithm developed in one age group may have limited performance in another. [2,11] Data quality and heterogeneity also remain important challenges. Differences in ECG acquisition protocols, equipment, sampling rates, signal quality, and methods of ECG annotation may affect model performance. [7,11]

Most available studies focus on the diagnostic performance of AI models, whereas considerably less evidence is available regarding their actual impact on clinical decision-making and patient outcomes. High sensitivity or AUROC does not automatically translate into improved patient care. Therefore, before AI-ECG can be implemented in routine clinical practice, prospective studies are needed to evaluate its safety, clinical utility, and impact on the diagnostic and therapeutic process.

Conclusions

Artificial intelligence represents a promising tool supporting the development of pediatric electrocardiography. Current research indicates that machine learning and deep learning models can support automated ECG interpretation and the detection of rhythm and conduction disorders, long QT syndrome, and congenital heart disease. The use of AI-ECG for the indirect assessment of left ventricular function and the prediction of adverse cardiovascular events is also gaining increasing attention.

The greatest potential value of AI lies in its ability to detect complex and subtle patterns in ECG recordings that may be difficult to identify through standard assessment. At the same time, the current level of evidence does not support considering AI a substitute for conventional cardiac diagnostics. Limitations related to the size and representativeness of datasets, age-dependent variability in ECG parameters, model generalizability, and the limited number of prospective and multicenter studies highlight the need for further validation.

In the coming years, the development of AI in pediatric electrocardiography should focus not only on improving algorithmic accuracy but also on interpretability, safety, and applicability in real-world clinical settings. It will be particularly important to determine whether the use of AI-ECG leads to earlier disease detection, improved risk stratification, and more informed diagnostic decision-making. At present, AI-ECG should primarily be regarded as a tool to support clinicians, with its clinical value depending not only on the technical performance of the model but also on data quality, appropriate validation, and effective integration into the care of pediatric patients.

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