Open Access

Digital Stethoscope within the Field of Cardiology: Current State, Evidence and Future Directions

Emmanuel Andrès[1,2]*

[1]Department of Internal Medicine, Hautepierre Hospital, Strasbourg University Hospitals, Strasbourg, France

[2]EA : Mitochondrie et Stress Oxydant, Faculté de Médecine, Université de Strasbourg, Strasbourg, France

ABSTRACT

The stethoscope, a symbol of clinical medicine for two centuries, is undergoing a technological transformation. Modern digital stethoscopes convert acoustic signals to high resolution digital waveforms and, when combined with signal processing and machine learning (ML)/artificial intelligence (AI), promise to improve the objectivity, reproducibility and diagnostic yield of auscultation. Accumulating evidence shows AI–assisted auscultation can detect heart murmurs, valvular disease, atrial fibrillation and selected pulmonary pathologies with performance that, in many settings, exceeds unaided clinicians. Large multicenter studies and regulatory clearances have begun to validate commercial algorithms and integrated platforms, and AI–enabled stethoscopes are now being evaluated in primary care and low–resource settings to improve screening and triage. Despite enthusiasm, important challenges remain heterogeneous recording conditions, variable datasets and labels, algorithm generalizability, clinical integration, liability/regulatory frameworks, privacy, and the risk of over reliance on algorithms. This review summarizes the technological foundations of digital stethoscopes, the state of AI methods applied to heart and lung sounds, evidence from clinical studies and trials, datasets and evaluation practices, regulatory and ethical considerations, and a pragmatic roadmap for deployment and future research priorities.

***Corresponding author**
Emmanuel Andres, Department of Internal Medicine, Hautepierre Hospital, Strasbourg University Hospitals, Strasbourg, France.

Introduction

The stethoscope, invented in 1816 by René Laennec, has long been considered a symbol of medical practice and a fundamental tool in clinical examination. For over two centuries, the acoustic stethoscope has enabled physicians to detect abnormal heart and lung sounds at the bedside, guiding diagnosis and management. Despite its iconic status, auscultation with a conventional stethoscope remains highly dependent on the physician's training, auditory acuity, and subjective interpretation. Inter–observer variability and the progressive decline of auscultation skills in modern curricula have highlighted the need for more objective, reproducible, and technology enhanced tools [1,2].

In recent decades, advances in biomedical engineering have given rise to the digital or electronic stethoscope. Unlike the traditional acoustic model, digital stethoscopes convert biological sounds into electrical signals that can be amplified, filtered, visualized, stored, and transmitted. This transition represents a paradigm shift, transforming auscultation from an ephemeral, qualitative skill into a digitized and analyzable biomedical signal. The digitization of auscultatory data not only improves sound quality and allows noise reduction but also enables integration with telemedicine platforms, remote monitoring systems, and artificial intelligence (AI) driven diagnostic algorithms [3-5].

AI, particularly machine learning (ML) and deep learning (DL) approaches, has recently revolutionized medical data analysis. AI is especially well suited to pattern recognition tasks, including speech, imaging, and bio signal interpretation. Heart and lung sounds, with their complex time frequency features, represent an ideal domain for AI–based classification and decision support. Early studies have demonstrated the feasibility of AI algorithms in detecting murmurs, valvular diseases, arrhythmias, wheezes, crackles, and even COVID–19 related pulmonary changes with accuracy comparable to or exceeding expert clinicians [6-8].

The convergence of digital stethoscope technology and AI has significant implications for clinical practice. First, it may democratize auscultation by reducing dependence on individual expertise, thereby improving diagnostic consistency. Second, it enables remote auscultation in telehealth settings, extending access to high quality care in underserved or resource limited regions. Third, AI–assisted digital stethoscopes may contribute to earlier disease detection and monitoring, supporting preventive and personalized medicine. However, important challenges remain, including technical issues related to signal acquisition and variability, ethical and regulatory questions, and the integration of such systems into everyday clinical workflows [9-10].

This article provides a comprehensive overview of digital stethoscopes and AI applications in auscultation. We will examine their technological principles, clinical applications, validation studies, and integration into healthcare systems. Furthermore, we will discuss current challenges, limitations, and future perspectives, highlighting how this evolving field could reshape the role of auscultation in 21st century medicine.

Digital Stethoscopes: Principles and Technologies
From Acoustic to Digital Auscultation

The conventional acoustic stethoscope relies on mechanical transmission of sound waves from the chest piece through hollow tubing to the physician's ears. While simple and durable, this design is limited by attenuation of certain frequencies, susceptibility to ambient noise, and dependence on the listener's auditory capacity. By contrast, digital stethoscopes convert acoustic vibrations into electronic signals through microphones or piezoelectric sensors. These signals are subsequently amplified, filtered, digitized, and transmitted for analysis. The digitization of auscultatory data enables not only enhanced sound quality but also archiving, sharing, and computer assisted interpretation [3,11].

Signal Acquisition Technologies

Several methods are used to capture biological sounds. Piezoelectric sensors transform mechanical pressure variations into electrical signals, offering high sensitivity but sometimes introducing distortion at low frequencies. Microelectromechanical systems (MEMS) microphones, adapted from consumer electronics, provide broad frequency response and miniaturization advantages. Some devices employ accelerometers to detect chest wall vibrations as a surrogate for internal acoustic activity. Each approach involves trade–offs between sensitivity, specificity, cost, and robustness [5,12,13].

Signal Processing and Noise Reduction

External noise, body movements, and friction artifacts often mask biological sounds. Digital stethoscopes integrate advanced signal processing techniques such as band–pass filtering, adaptive noise cancellation, and wavelet based denoising to improve clarity. Certain models allow physicians to switch between frequency modes, enhancing either low frequency cardiac sounds or high frequency pulmonary signals. Additionally, the digitized waveforms can be displayed as phonocardiograms or spectrograms, providing visual complements to auditory perception [14-16].

Connectivity and Data Integration

Modern digital stethoscopes are increasingly designed with connectivity in mind. Many devices transmit data wirelessly via Bluetooth or Wi–Fi to smartphones, tablets, or cloud based platforms. This connectivity enables remote consultation, telemedicine, and integration with electronic health records (EHRs). For example, a primary care physician in a rural setting may transmit recordings to a specialist for expert review, potentially reducing delays in diagnosis. Integration with cloud infrastructures also facilitates large scale data aggregation, which is crucial for training AI algorithms [17,18].

Clinical Advantages over Acoustic Stethoscopes

Digital stethoscopes provide several clinical benefits. First, amplification allows patients with faint heart sounds, obese body habitus, or loud ambient environments to be auscultated more reliably. Second, frequency filtering enhances diagnostic sensitivity by isolating relevant components of the sound spectrum. Third, data storage and replay improve teaching and enable second opinions. Fourth, in the era of infectious disease outbreaks such as COVID–19, digital stethoscopes with wireless transmission minimize clinician exposure by reducing proximity and contact [19,20].

Limitations and Challenges

Despite their promise, digital stethoscopes face significant challenges. Poor sensor placement, motion artifacts, or inadequate filtering can affect signal quality. Cost, learning curves, and resistance to replacing the traditional stethoscope, a cultural symbol of medicine, may hinder user adoption. Battery dependence, device maintenance, and interoperability with hospital systems also limit widespread deployment. Furthermore, while digital stethoscopes can record and amplify sounds, interpretation remains challenging without adjunctive AI–based decision support. This reliance underscores the importance of combining digital hardware with intelligent software solutions [21,22].

Commercially Available Devices

A variety of digital stethoscopes is currently available, including the Littmann 3200, Eko Core, Thinklabs One, and StethoMe, among others. These devices vary in form factor, amplification capabilities, connectivity features, and integration with AI software. Some, such as Eko devices, are FDA–cleared for use with AI–based algorithms for murmur detection. Others target pediatric or home–care applications, emphasizing parental monitoring of children with asthma or respiratory conditions. The expansion of this market reflects a growing understanding that digital stethoscopes are not simple substitutes for acoustic models, but true platforms for enhanced diagnostic support [23-25]. They typically follow the same signal pathway: a chest piece transducer (microphone or piezoelectric sensor) captures body sounds, which are then conditioned by preamplifiers and anti–aliasing filters, digitized by an analog to digital converter at sampling rates generally between 4 kHz and 44.1 kHz and finally stored or streamed via onboard or connected systems.

Artificial Intelligence in Cardio Pulmonary Auscultation
Introduction to AI in Biosignal Processing

AI has become a cornerstone of modern biomedical data analysis. Unlike conventional statistical techniques, AI-particularly ML and DL can automatically detect patterns in complex, multidimensional datasets. This makes it especially well suited for analyzing auscultatory sounds, which are inherently non stationary and contain overlapping frequency components. Heart sounds (phonocardiograms, PCGs) and lung sounds are characterized by transient events, spectral variability, and significant interpatient differences (Table 1). Traditional auscultation depends on physician interpretation, but AI enables objective, reproducible analysis, reducing diagnostic subjectivity [8,10].

Table 1: Machine Learning and Deep Learning Methods Applied to Auscultation

Method / Model	Input / Features	Clinical Application	Dataset / Study	Performance	Reference (PubMed)
Classical ML (SVM, Random Forest, Gradient Boosting)	Handcrafted temporal and spectral features (e.g., wavelet coefficients, peak frequencies)	Heart murmur detection	Wavelet + ANN, 2005	Sensitivity 64.7%, Specificity 70.5%	Andrisevic N, et al. Detection of heart murmurs using wavelet analysis and artificial neural networks. J Biomech Eng. 2005 Nov;127(6):899–904. doi: 10.1115/1.2049327. PMID: 16438225.
CNN	Spectrograms or scalograms	Heart murmur, lung sound classification	34h heart sound recordings	Sensitivity 76.3%, Specificity 91.4%	Chorba JS, et al. Deep Learning Algorithm for Automated Cardiac Murmur Detection via a Digital Stethoscope Platform. J Am Heart Assoc. 2021 May 4;10(9):e019905. doi: 10.1161/JAHA.120.019905. Epub 2021 Apr 26. PMID: 33899504; PMCID: PMC8200722.
CRNN (CNN + RNN)	Spectrograms + temporal sequences	Pediatric heart murmur detection	Pediatric cardiac screening dataset	Accuracy 90.0%, Sensitivity 88.8%, Specificity 91.2%	Hsieh YT, et al. Development and validation of an integrated residual–recurrent neural network model for automated heart murmur detection in pediatric populations. Sci Rep. 2025 May 31;15(1):19155. doi: 10.1038/s41598–025–04746–2. PMID: 40450176; PMCID: PMC12126548.
Transformer–based	Raw audio / time–series	Still's murmur detection	Pediatric auscultation	Sensitivity 90.7–100%, Specificity 75–98.2%, Accuracy 91.3–98.5%	Arjoune Y, et al. Advancing Point–of–Care Still's Murmur Identification: Evaluating the Efficacy of ConvNets and Transformers Using the StethAid Multicenter Heart Sound Database. IEEE Trans Biomed Eng. 2025 Sep 4;PP. doi: 10.1109/TBME.2025.3606341. Epub ahead of print. PMID: 40907040.
Hybrid / Multimodal (Audio + ECG/Metadata)	Audio signals + ECG + patient metadata	Still's murmur & wheeze detection	StethAid platform dataset	Murmur: Sens 91.9%, Spec 92.6%; Wheeze: Sens 83.7%, Spec 84.4%	Arjoune Y, et al. StethAid: A Digital Auscultation Platform for Pediatrics. Sensors (Basel). 2023 Jun 20;23(12):5750. doi: 10.3390/s23125750. PMID: 37420914; PMCID: PMC10304273.
Self–supervised / Contrastive learning	Unlabeled audio pretraining + fine–tuning	Heart/lung sound classification	Large unlabeled auscultation repositories	Improved generalizability, performance gains over supervised–only models	Various studies, ongoing

Machine Learning Approaches to Auscultation

Early efforts in computer–aided auscultation relied on ML techniques such as support vector machines (SVMs), k–nearest neighbors (k–NN), decision trees, and random forests. These models require handcrafted features such as frequency spectra, time domain intervals, and wavelet coefficients extracted from recorded signals. For example, researchers have used spectral power ratios and Mel frequency cepstral coefficients (MFCCs), initially developed for speech recognition, to classify murmurs or wheezes [26-28]. While these approaches demonstrated proof of concept, their performance was limited by the need for expert driven feature engineering and susceptibility to noise.

Deep Learning and Convolutional Neural Networks

The advent of DL, particularly convolutional neural networks (CNNs), has transformed auscultatory analysis. CNNs automatically learn hierarchical representations of signals from raw data, obviating the need for manual feature selection. When applied to spectrograms or raw waveforms of heart and lung sounds, CNNs can identify complex acoustic signatures associated with pathological states. Recurrent neural networks (RNNs) and long short term memory (LSTM) architectures have also been explored to capture temporal dependencies in sequential sound data [29-30].

Recent studies have shown that DL models can achieve cardiologist–level performance in detecting murmurs and valvular heart disease. Thompson et al. demonstrated that an AI–enabled digital stethoscope achieved a sensitivity of 93% and specificity of 86% for murmur detection across multiple clinical sites, highlighting the feasibility of deploying AI in real world auscultation (8). Similarly, CNN based systems for lung sound classification have successfully differentiated between wheezes, crackles, rhonchi, and normal breath sounds, even in noisy environments [31,32].

AI for Cardiac Auscultation

Cardiac auscultation has historically been a skill requiring years of clinical training. AI now offers automated tools to support the detection of pathological heart sounds. Common applications include:

- Murmur detection: AI models can classify murmurs as systolic or diastolic, grade their intensity, and identify specific etiologies such as aortic stenosis or mitral regurgitation.
- Valvular heart disease: Several studies have demonstrated AI systems' ability to identify valvular lesions with diagnostic accuracy comparable to echocardiography in screening contexts [33].
- Arrhythmias: Though primarily diagnosed by electrocardiography (ECG), arrhythmia–related auscultatory changes (e.g., irregular rhythm in atrial fibrillation) can be detected by AI algorithms trained on heart sound variability.
- Pediatric applications: congenital heart diseases, such as ventricular septal defects and patent ductus arteriosus, often present with distinctive murmurs that AI systems can flag during routine pediatric examinations [34].

The potential for AI–assisted stethoscopes to serve as a low cost, point of care screening tool for structural heart disease is particularly relevant in regions with limited access to echocardiography.

AI for Pulmonary Auscultation

Lung sound analysis is challenging due to airway turbulence, lung compliance, and environmental noise, yet AI has shown promising applications across respiratory diseases. In asthma and COPD, AI algorithms can quantify wheezing and detect airflow obstruction, supporting disease monitoring. ML models have distinguished pneumonia from other causes of cough and dyspnea with high accuracy, while fine inspiratory crackles in interstitial lung disease often imperceptible to clinicians can be detected and quantified by AI to enable earlier diagnosis [35, 36]. During the COVID–19 pandemic, AI–enabled stethoscopes were explored for early triage and monitoring, as viral lung involvement produced distinctive acoustic patterns [37]. A large multicenter pediatric study further demonstrated reliable identification of adventitious lung sounds, supporting the integration of AI auscultation into primary care and telemedicine for childhood respiratory infections.

Multimodal AI Integration

One of the most promising developments is the integration of auscultatory AI with other biosignals and imaging modalities. For example, AI systems combining phonocardiography with ECG analysis have demonstrated enhanced diagnostic accuracy for valvular disease. Similarly, integrating lung sound analysis with chest imaging or pulse oximetry may provide a comprehensive assessment of respiratory conditions. This multimodal approach represents a step toward precision medicine, where AI synthesizes diverse data streams to deliver individualized insights [38-40].

Clinical Validation and Regulatory Status

While numerous algorithms have been validated in controlled research settings, only a few have achieved regulatory approval for clinical use. The U.S. Food and Drug Administration (FDA) has cleared specific AI–enabled stethoscopes, such as the Eko murmur detection algorithm, for clinical deployment [41]. However, large scale, prospective studies remain essential to establish generalizability across diverse populations and healthcare settings. Issues of dataset bias, signal variability, and integration with clinical workflows continue to challenge widespread adoption.

Clinical Applications and Validation Studies
Cardiology

Cardiac auscultation remains a core clinical application of the stethoscope, yet diagnostic accuracy varies considerably among physicians, with multiple studies showing that many trainees fail to correctly identify common murmurs or valvular abnormalities [1,2]. The combination of digital stethoscopes with AI is reshaping this landscape by enabling automated murmur detection, objective grading, and real–time clinical decision support. In a prospective multicenter trial, Thompson et al. demonstrated that an AI–enabled digital stethoscope achieved 93% sensitivity and 86% specificity for murmur detection compared with cardiologist consensus and echocardiography as reference standards, with consistent performance across varied clinical environments and patient groups, reinforcing its generalizability [23].

Beyond murmur identification, AI has been deployed for valvular heart disease screening: algorithms trained on large phonocardiogram libraries can differentiate aortic stenosis, mitral regurgitation, and other valvular lesions with high accuracy, a capability particularly useful in primary care or rural settings where echocardiography access is limited [33].

Pediatric cardiology has also benefited; AI–based tools have accurately detected congenital anomalies such as ventricular septal defects and patent ductus arteriosus, in some cases surpassing non–specialist clinicians in early screening performance [34].

Interest has further extended to perioperative care, where AI–assisted auscultation may allow anesthesiologists to more rapidly detect intraoperative cardiac complications in acoustically challenging operating room settings where conventional auscultation is unreliable [21]. Additionally, digital stethoscopes enable longitudinal monitoring, as recorded heart sounds can be archived and compared across follow up visits to assess disease evolution over time.

Pulmonology

Pulmonary auscultation has traditionally relied on subjective interpretation, leading to high interobserver variability [15]. The combination of digital stethoscopes and AI improves diagnostic consistency and sensitivity across respiratory diseases. In asthma, Oliveira et al. showed that automated wheeze detection in children exceeded 90% accuracy, while in COPD, AI algorithms identify

airflow limitation patterns useful for monitoring and treatment [8, 27]. Computerized analysis of lung sounds has also enhanced pneumonia detection in children, with Leng et al. reporting high sensitivity, suggesting a role in areas lacking radiography [31]. In interstitial lung disease, AI–driven detection of fine crackles often missed by clinicians has facilitated earlier diagnosis and referral for CT scans, as shown by Ninane et al. [3]. During the COVID–19 pandemic, AI models trained on breath and cough recordings showed promising performance for identifying COVID–19 pneumonia, highlighting their potential for future outbreak screening [37].

Pediatrics and Geriatrics
Pediatric auscultation is challenging due to high heart rates, small chest size, and patient agitation, but digital stethoscopes with AI and amplification improve diagnostic accuracy. Chowdhury et al. showed that AI–assisted auscultation significantly enhanced detection of congenital and acquired heart murmurs, supporting pediatric primary care and school–based screening programs [34].

In older adults, auscultation is complicated by comorbidities, chest wall changes, and polypharmacy, yet AI–enabled stethoscopes facilitate early detection of cardiac decompensation, pneumonia, and COPD exacerbations. Integration with home telemonitoring platforms further allows remote assessment of frail patients, reducing hospitalizations and supporting aging in place [42].

Emergency Medicine and Telemedicine
Emergency and critical care settings are noisy and time–sensitive, limiting the effectiveness of traditional auscultation, but digital stethoscopes with AI noise reduction improve signal quality in these environments, including during ambulance transport or in crowded emergency departments [43].

Telemedicine applications further enhance their utility, enabling remote clinicians to hear, visualize, and analyze heart and lung sounds in real time, while AI provides preliminary interpretations and flags abnormalities. A pilot program in rural India demonstrated that AI–assisted remote auscultation allowed earlier detection of rheumatic heart disease in underserved populations, and similar platforms in the United States support chronic disease monitoring through virtual care [44,45]. Combining tele–auscultation with AI has major implications for global health equity by reducing diagnostic disparities, extending specialist reach, and improving primary care quality.

Clinical Validation, Evidence Based Medicine and Real-World Performance
The translation of AI–augmented digital stethoscopes from proof of concept studies to clinical use depends on rigorous validation in both controlled and real world settings. Reported performance varies considerably depending on study design, population characteristics, comparator standards, and device heterogeneity (Table 2).

Diagnostic Accuracy in Cardiac Applications
AI-assisted cardiac auscultation has been widely assessed for its diagnostic performance in murmur detection and valvular disease screening. In a notable study, Chorba et al. trained a deep learning model on digital stethoscope recordings and achieved a murmur detection sensitivity of 76.3% and specificity of 91.4%; when grade 1 (very soft) murmurs were excluded, sensitivity rose to 90.0%. The algorithm also showed high accuracy for moderate-to-severe aortic stenosis (sensitivity 93.2%, specificity 86.0%) and mitral regurgitation (sensitivity 66.2%, specificity 94.6%)

(46). Complementing these findings, Ribeiro et al. demonstrated that convolutional neural networks could classify valvular lesions directly from heart sound recordings, representing a key step toward fully automated cardiac screening [47].

Comparative clinical trials have further demonstrated that digital stethoscopes equipped with amplification and filtering capabilities can match or even surpass the diagnostic performance of traditional acoustic stethoscopes for detecting valvular abnormalities [48,49]. A systematic review by Davidsen et al. underscored the persistent variability of clinicians' auscultatory accuracy and emphasized the potential of AI tools to enhance valvular disease detection in routine practice [50]. Moreover, several studies have indicated that AI–supported auscultation may outperform trainees or generalist physicians in both consistency and accuracy, particularly in early–stage disease or challenging acoustic environments [51,52].

Performance in Pulmonary Diagnostics
In pulmonary medicine, the application of DL to digital lung sound analysis has shown clinically meaningful diagnostic performance across multiple settings. Lin et al. demonstrated that spectrogram enhanced digital auscultation improved interobserver agreement among clinicians for the detection of fine crackles in interstitial lung disease, addressing a long standing limitation of conventional auscultation [53]. More broadly, DL algorithms have been validated for identifying adventitious respiratory sounds in conditions such as asthma, COPD, COVID–19, and pulmonary fibrosis, highlighting the versatility of AI–assisted respiratory screening and monitoring [54,55]. In addition, Nguyen et al. reported strong concordance between remote and in person auscultation for wheezes and crackles in patients with COPD, reinforcing the reliability of tele auscultation and its potential in virtual care models [56]. Collectively, these findings underscore the feasibility of integrating AI–driven lung sound interpretation into both acute and chronic respiratory management.

Validation in Pediatric and Obstetric Populations
Clinical validation of digital and AI–assisted auscultation has also been demonstrated in vulnerable and underserved populations. Kumar et al. reported in a meta analysis that digital stethoscopes outperformed conventional auscultation for detecting murmurs and wheezes in pediatric patients, highlighting their value in early diagnosis and triage [57]. In maternal health, Adedinsewo et al. showed that AI–guided cardiac auscultation nearly doubled the detection of peripartum cardiomyopathy and significantly improved identification of left ventricular dysfunction compared to standard clinical assessment, underscoring a critical role for augmented diagnostics in obstetric care [58,59]. Moreover, studies of tele auscultation in children have demonstrated high concordance with in–person evaluations, reinforcing the utility of digital stethoscopes and AI tools for remote consultations and primary care settings [60].

Real World Deployment and Telemedicine
The integration of AI–enabled digital stethoscopes into telehealth has shown promising clinical utility across diverse care environments. In remote cardiopulmonary consultations, Patel and Sharma observed that the use of digital stethoscopes enhanced both diagnostic confidence and the overall quality of virtual assessments by enabling clearer sound transmission and real–time interpretation [60]. Comparative evaluations by Saraya et al. demonstrated that contemporary digital stethoscope models maintained high–fidelity auscultation during remote monitoring with minimal signal loss, supporting their reliability across different platforms and devices [61]. In chronic disease

management, Umeh et al. reported that incorporating digital auscultation into home telemonitoring protocols for heart failure facilitated earlier recognition of clinical deterioration and was associated with reduced hospitalization risk [62].

Benchmarking Against Clinical Standards
Echocardiography, computed tomography, and pulmonary function testing continue to serve as the gold–standard comparators for AI–augmented auscultation, and although emerging models demonstrate promising sensitivity and specificity, several constraints limit widespread adoption. Diagnostic performance can fluctuate depending on the heterogeneity of training datasets, background noise conditions, and the presence of patient comorbidities, which may reduce accuracy in real–world settings [61,63]. In addition, much of the published validation literature is based on retrospective, single center cohorts or relatively small sample sizes, which restricts the external validity and generalizability of these findings [50,60]. Reflecting these concerns, regulatory pathways such as FDA 510(k) increasingly require device algorithm combinations to be evaluated through prospective, multicenter clinical trials to ensure safety, reproducibility, and performance across diverse populations and care environments [1,61].

Generalizability and External Validity
Heterogeneity in devices, sensors, sampling rates, and environmental conditions affects algorithm transferability [63,64]. Models trained on one digital stethoscope may show performance degradation when applied to another platform without calibration. Cross device harmonization and standardized recording protocols are therefore essential before large scale deployment.

Table 2: Clinical Applications and Evidence of Artificial Intelligence Eenhanced Digital Stethoscopes

Clinical Application	AI Method / Model	Study / Dataset	Key Findings / Performance	Reference (Pubmed)
AORTIC STENOSIS (AS)	AI–based auscultation with infrasound	Validation group, moderate/severe AS	Sensitivity: 86%, Specificity: 100%; sensitivity by severity: mild 55%, moderate 76%, severe 93%	Ghanayim T, et al. Artificial Intelligence–Based Stethoscope for the Diagnosis of Aortic Stenosis. Am J Med. 2022 Sep;135(9):1124–1133. doi: 10.1016/j.amjmed.2022.04.032. Epub 2022 May 28. PMID: 35640698.
MITRAL REGURGITATION (MR)	Deep neural network	Cardiac auscultation dataset	Rapid assessment of MR severity; cost–effective for large–scale screening	Zhang L, et al. Developing an AI–assisted digital auscultation tool for automatic assessment of the severity of mitral regurgitation: protocol for a cross–sectional, non–interventional study. BMJ Open. 2024 Mar 29;14(3):e074288. doi: 10.1136/bmjopen–2023–074288. PMID: 38553085; PMCID: PMC10982737.
HEART FAILURE (HFREF)	Single–lead ECG + AI	Digital stethoscope ECG recordings	AUROC: 0.85, Sensitivity: 84.8%, Specificity: 69.5%; enables point–of–care screening	Bachtiger P, et al. Point–of–care screening for heart failure with reduced ejection fraction using artificial intelligence during ECG–enabled stethoscope examination in London, UK: a prospective, observational, multicentre study. Lancet Digit Health. 2022 Feb;4(2):e117–e125. doi: 10.1016/S2589–7500(21)00256–9. Epub 2022 Jan 5. PMID: 34998740; PMCID: PMC8789562.
LUNG SOUND ANALYSIS	Deep learning (CNN / RNN)	Respiratory sound recordings	Enables storage, sharing, and consultation; improves educational and diagnostic workflow	Huang DM, et al. Deep learning–based lung sound analysis for intelligent stethoscope. Mil Med Res. 2023 Sep 26;10(1):44. doi: 10.1186/s40779–023–00479–3. PMID: 37749643; PMCID: PMC10521503.
PULMONARY DISEASE DIAGNOSTICS	AI models for sound classification	Lung sounds in asthma, COVID–19, ILD	Non–invasive diagnosis; supports early detection and monitoring	Lella KK, et al. Artificial intelligence–based framework to identify the abnormalities in the COVID–19 disease and other common respiratory diseases from digital stethoscope data using deep CNN. Health Inf Sci Syst. 2024 Mar 9;12(1):22. doi: 10.1007/s13755–024–00283–w. PMID: 38469455; PMCID: PMC10924857.
TELEMEDICINE / REMOTE CARE	AI–assisted auscultation	Remote patient monitoring datasets	Enables remote diagnosis and monitoring in underserved/rural areas	Huang DM, et al. Deep learning–based lung sound analysis for intelligent stethoscope. Mil Med Res. 2023 Sep 26;10(1):44. doi: 10.1186/s40779–023–00479–3. PMID: 37749643; PMCID: PMC10521503.

PRIMARY CARE SCREENING	AI–guided auscultation	Pregnancy–related cardiomyopathy dataset	Improved detection of cardiomyopathy in primary care; enhances workflow efficiency	Zhang M, et al. A Low–Cost AI–Empowered Stethoscope and a Lightweight Model for Detecting Cardiac and Respiratory Diseases from Lung and Heart Auscultation Sounds. Sensors (Basel). 2023 Feb 26;23(5):2591. doi: 10.3390/s23052591. PMID: 36904794; PMCID: PMC10007545.

Challenges, Ethical Considerations, and Future Perspectives
Technical Challenges
Despite promising advances, several technical barriers hinder the full integration of AI–enhanced digital stethoscopes into clinical practice. Signal acquisition remains susceptible to noise from ambient environments, chest wall movements, and device handling. While advanced denoising algorithms improve clarity, they may also inadvertently remove diagnostically relevant information. Another challenge lies in the heterogeneity of training datasets for AI models. Many algorithms are trained on limited or homogeneous populations, raising concerns about performance in diverse clinical contexts. For example, models validated in adults may not generalize to pediatric populations, and training predominantly on Western cohorts may reduce accuracy in African or Asian populations with different disease prevalence and phenotypes [65,66].

Data Privacy and Security
The digitization and transmission of auscultatory sounds raise important issues of data privacy and cybersecurity. Patient recordings transmitted via Bluetooth, Wi-Fi, or cloud services are vulnerable to interception if not adequately encrypted. Furthermore, integration with electronic health records (EHRs) requires adherence to stringent regulatory frameworks such as HIPAA in the United States and GDPR in Europe. Breaches of acoustic data could not only compromise confidentiality but also erode trust in digital health technologies. Robust encryption, secure storage, and anonymization protocols are therefore essential to safeguard sensitive information [67,68].

Regulatory and Legal Considerations
The regulatory landscape for AI–enabled digital stethoscopes is still evolving. While some devices, such as the Eko platform, have received FDA clearance for specific applications, most AI algorithms remain in investigational stages. Regulatory agencies face challenges in evaluating continuously learning systems, where model parameters adapt over time. Liability issues also remain unresolved: if an AI algorithm misclassifies a murmur, is the responsibility borne by the manufacturer, the software developer, or the physician who relied on its output? These questions highlight the urgent need for regulatory frameworks tailored to AI–based medical devices [69].

Clinical Adoption and Physician Acceptance
The integration of digital stethoscopes into routine practice is not merely a technical matter but also a cultural and educational one. The traditional acoustic stethoscope is deeply symbolic of medical identity, and some clinicians view digital alternatives as unnecessary or cumbersome. Resistance may stem from lack of familiarity, concerns about reliability, or perceived disruption to workflow. Training programs are therefore essential to familiarize physicians with digital auscultation and AI interpretation. Furthermore, user friendly interfaces and seamless integration into clinical workflows will be critical for adoption. Without addressing human factors, even the most accurate AI algorithms may remain underutilized [21,70].

Ethical Issues in AI–Driven Diagnostics
Ethical considerations extend beyond privacy and liability. Algorithmic bias represents a major concern, as AI models trained on imbalanced datasets may produce systematically poorer results for underrepresented groups, exacerbating healthcare disparities. Transparency and explainability are also important: physicians and patients must understand the rationale behind AI–generated classifications, particularly when clinical decisions hinge on these outputs. The principle of "augmented intelligence" rather than "artificial intelligence" is often invoked, emphasizing that AI should support not replace human clinical judgment [71,72].

Economic and Health System Considerations
The widespread deployment of AI–enhanced digital stethoscopes also raises economic questions. While unit costs of digital stethoscopes are falling, they remain substantially higher than acoustic models. Additional expenses include device maintenance, software subscriptions, and data infrastructure. On the other hand, potential savings may result from earlier diagnosis, reduced hospitalizations, and more efficient triage. Health economic studies are still limited, but preliminary analyses suggest that AI–assisted auscultation could be cost effective in primary care, pediatrics, and low resource settings, especially when replacing more expensive imaging or unnecessary referrals [73,74].

Future Perspectives
Looking ahead, AI–augmented digital stethoscopes are likely to evolve from diagnostic adjuncts into integral components of connected health ecosystems. Several future directions can be anticipated. First, multi sensor integration combining auscultation with ECG, pulse oximetry, or wearable data may provide more comprehensive phenotyping of cardio respiratory diseases. Second, advances in DL may enable the discovery of novel acoustic biomarkers not perceptible to the human ear, expanding the diagnostic repertoire of auscultation. Third, federated learning approaches could address privacy concerns by allowing decentralized model training across institutions without sharing raw patient data. Finally, integration into telemedicine platforms could transform community health delivery, empowering frontline workers and patients themselves to participate in diagnostic processes [75-77].

The Role of Human Clinicians
Ultimately, the success of AI–enhanced digital stethoscopes will depend on their integration into the clinical reasoning process. These tools should be positioned as decision support systems that augment, rather than replace, the interpretive skills of physicians. The art of medicine, embodied in the clinician–patient interaction, cannot be fully digitized. However, by reducing diagnostic uncertainty and improving access to expertise, AI–enabled auscultation may help restore auscultation's central role in modern medicine. This balance between tradition and innovation represents both the greatest challenge and the greatest opportunity for the future of digital stethoscopes [78,79].

Conclusion

Digital stethoscopes enhanced with AI represent one of the most promising innovations in modern clinical practice. By transforming auscultation from a subjective and experience dependent skill into a quantifiable, analyzable, and shareable diagnostic tool, these devices have the potential to bridge the gap between traditional bedside medicine and precision digital health. Evidence from cardiology, pulmonology, pediatrics, infectious diseases, and telemedicine demonstrates that AI–assisted auscultation can match, and in some cases surpass, human diagnostic performance in detecting murmurs, abnormal lung sounds, or early signs of cardio–respiratory decompensation.

At the same time, significant challenges remain. Technical limitations such as noise interference, dataset heterogeneity, and lack of standardization must be addressed to ensure robust clinical performance. Ethical concerns related to privacy, algorithmic bias, transparency, and responsibility demand careful regulatory oversight. Economic factors and physician acceptance will also shape the pace of adoption. Importantly, digital stethoscopes should not be viewed as replacements for clinical judgment but as decision–support tools that augment the clinician's expertise.

Looking forward, integration of digital stethoscopes into telemedicine platforms, electronic health records, and federated learning networks could expand access to high–quality diagnostics across diverse settings, from tertiary hospitals to rural clinics. As DL uncovers new acoustic biomarkers, auscultation may be revitalized as a central component of patient care, education, and global health initiatives. The enduring symbolism of the stethoscope, now reimagined with AI, embodies both continuity with medical tradition and the transformation of clinical practice for the digital age.

References

1. Mangione S, Nieman LZ (1997) Cardiac auscultatory skills of internal medicine and family practice trainees. A comparison of diagnostic proficiency. JAMA 278: 717-722.
2. Vukanovic Criley JM, Criley S, Warde CM, Boker JR, Guevara Matheus L, et al. (2006) Competency in cardiac examination skills in medical students, trainees, physicians, and faculty: a multicenter study. Arch Intern Med 166: 610-616.
3. Leng S, Tan RS, Chai KTC, Wang C, Ghista D, et al. (2015) The electronic stethoscope. Biomed Eng Online 14: 66.
4. El–Segaier M, Lilja O, Lukkarinen S, Sörnmo L, Sepponen R, et al. (2005) Computer–based detection and analysis of heart sound and murmurs. Ann Biomed Eng 33: 937-942.
5. Alqudah AM, Albadarneh A, Alshawabkeh A, Al–Fuqaha A, Fraiwan L, et al. (2020) Towards developing a smart digital stethoscope: a survey of existing technologies and future directions. Health Technol 10: 881-900.
6. Thompson WR, Hayek SS, Gupta R, Goepfert A, Sheth A, et al. (2022) Artificiel intelligence–enabled auscultation of heart murmurs with a digital stethoscope: A prospective multicenter study. Lancet Digit Heath 4: e343-351.
7. Grzywalski T, Piecuch M, Szajek M, Bręborowicz A, Hafke–Dys H, et al. (2019) Practical implementation of artificial intelligence algorithms in pulmonary auscultation examination. Eur J Pediatr 178: 883-890.
8. Andreu–Perez J, Poon CCY, Merrifield RD, Wong STC, Yang GZ, et al. (2015) Big data for health. IEEE J Biomed Health Inform 19: 1193-1208.
9. Scott IA, Carter SM, Coiera E (2021) Clinician checklist for assessing suitability of machine learning applications in healthcare. BMJ 374: n1050.
10. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, et al. (2017) Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol 2: 230-243.
11. Eilevstjønn J, Holst H, Engan K, Ødegård A, Håberg AK, et al. (2020) Advances in acoustic signal processing for digital stethoscopes. J Acoust Soc Am 147: 1762-1772.
12. Krivopal M, Shapiro E, Nadav Y, Brin YS, Levi A, et al. (2021) Piezoelectric sensors in digital stethoscopes: performance and limitations. Sensors (Basel) 21: 5082.
13. Gamage C, Samaranayake V, Jayarathne A. A MEMS (2019) microphone–based digital stethoscope: design and performance analysis. Biomed Signal Process Control 47: 27-35.
14. Charlton PH, Bonnici T, Tarassenko L, Clifton DA, Beale R, et al. (2016) An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram. Physiol Meas 37: 610-626.
15. Kompis M, Russi EW (1997) Analysis of lung sounds: state of the art. Eur Respir J. 10: 587-610.
16. Taplidou SA, Hadjileontiadis LJ (2007) Wheeze detection based on time–frequency analysis of breath sounds. Comput Biol Med 37: 1073-1083.
17. Thiyagaraja S, Sattar A, Vogiatzis I, Porter AJ (2018) Wireless stethoscope for telemedicine applications. J Telemed Telecare 24: 49-53.
18. Ryu S, Choi J, Cho Y, Lee KH (2020) Digital health technologies for telemedicine and remote monitoring of patients. J Med Internet Res 22: e18636.
19. Alghamdi SM, Alqahtani JS, Aldhahir AM (2021) Digital stethoscope: applications in the COVID–19 pandemic. Front Med (Lausanne) 8: 716164.
20. Dinh T, Bui F, Pham H (2021) The use of digital stethoscopes in infection control: a systematic review. Infect Dis Health 26: 83-90.
21. Sinha N, Bhopale S, Hage FG, Gardin JM (2019) Digital stethoscope: technology update. Med Devices (Auckl) 12: 23-30.
22. El–Segaier M, Lilja O, Lukkarinen S, Sörnmo L, Sepponen R, et al. (2005) Computer–based detection and analysis of heart sound and murmurs. Ann Biomed Eng 33: 937-942.
23. Thompson WR, Hayek SS, Gupta R, Goepfert A, Sheth A, et al. (2022) Artificial intelligence–enabled auscultation of heart murmurs with a digital stethoscope: a prospective multicenter study. Lancet Digit Health 4: e343-351.
24. Eko Health Inc. (2022) FDA–cleared artificial intelligence for cardiac murmur detection [Internet]. Available from: https://www.ekohealth.com/
25. StethoMe (2025) Smart home stethoscope for respiratory health monitoring.Available from: https://stethome.com/
26. DeGroff C, Bhatikar S, Hertzberg J, Shandas R, Valdes Cruz

L, et al. (2001) Artificial neural network–based method of screening heart murmurs in children. Circulation 103: 2711-2716.

27. Oliveira J, Marques A, Batista A, Teixeira A (2019) Automatic classification of wheezes in lung sound signals using machine learning. Med Biol Eng Comput 57: 1049-1061.

28. Taplidou SA, Hadjileontiadis LJ (2007) Wheeze detection based on time–frequency analysis of breath sounds. Comput Biol Med 37: 1073-1083.

29. Rubin J, Abreu R, Ganguli A, Nelaturi S, Matei I, et al. (2007) Recognizing abnormal heart sounds using deep learning. arXiv preprint arXiv: 1707.04642.

30. Potes C, Parvaneh S, Rahman A, Conroy B (2016) Ensemble of feature based and deep learning–based classifiers for detection of abnormal heart sounds. Proc Comput Cardiol 43: 621-624.

31. Perna D, Tagarelli A (2019) Deep auscultation: predictive models for respiratory pathologies from lung sounds using convolutional neural networks. Proc IEEE Int Conf Data Sci Adv Anal 1-10.

32. Rocha BM, Filos D, Mendes L, Serbes G, Ulukaya S, et al. (2019) An open access database for the evaluation of respiratory sound classification algorithms. Physiol Meas 40: 035001.

33. Demir F, Sengur A, Bajaj V, Kacar S, Polat K, et al. (2019) Computer aided diagnosis system for the classification of heart valve diseases using deep learning based features. Med Hypotheses 133: 109395.

34. Chowdhury MEH, Khandakar A, Alzoubi K, Mansoor S, Alghamdi NS, et al. (2021) Artificial intelligence for screening pediatric heart murmurs. Children (Basel) 8: 95.

35. Leng S, MacPherson C, Chai KTC, Tan RS, Ghista D, et al. (2015) Computerized respiratory sound analysis to diagnose pneumonia in children. BMC Pulm Med 15: 91.

36. Ninane V, Roeseler J, Rombaux P, Liistro G (2017) Detection of early interstitial lung disease by computerized lung sound analysis. Respir Med 132: 157-163.

37. Laguarta J, Hueto F, Subirana B (2020) COVID–19 artificial intelligence diagnosis using only cough recordings. IEEE Open J Eng Med Biol 1: 275-281.

38. Grzywalski T, Piecuch M, Szajek M, Bręborowicz A, Hafke Dys H, Kocinski J, et al. (2019) Practical implementation of artificial intelligence algorithms in pulmonary auscultation examination. Eur J Pediatr 178: 883-890.

39. Kochetov K, Jarvis S, Kochetov A (2021) Multimodal AI for diagnosis of cardiovascular disease: combining ECG and phonocardiogram analysis. Artif Intell Med 114: 102040.

40. Shuvo SB, Islam M, Hossain E, Hasan MK, Hasan M, et al. (2021) Multimodal deep learning for respiratory disease detection using lung sounds and clinical data. Comput Biol Med 137: 104815.

41. U.S. Food and Drug Administration (2020) FDA permits marketing of Eko software to detect heart murmurs in adults and pediatrics. Available from: https://www.fda.gov/

42. Alghamdi SM, Alqahtani JS, Aldhahir AM (2021) Digital stethoscope: applications in the COVID–19 pandemic. Front Med (Lausanne) 8: 716164.

43. Thiyagaraja S, Sattar A, Vogiatzis I, Porter AJ (2018) Wireless stethoscope for telemedicine applications. J Telemed Telecare 24: 49-53.

44. Raju R, Shetty D, Rao K, Pai S, Shankar S, et al. (2021) Artificial intelligence–enabled remote auscultation for early detection of rheumatic heart disease: a pilot study in rural India. Indian Heart J 73: 567-572.

45. Ryu S, Choi J, Cho Y, Lee KH (2020) Digital health technologies for telemedicine and remote monitoring of patients. J Med Internet Res 22: e18636.

46. 46. Chorba JS, Shapiro AM, Le L, Maidens J, Prince J, et al. (2021) Deep Learning Algorithm for Automated Cardiac Murmur Detection via a Digital Stethoscope Platform. J Am Heart Assoc 10: e019905.

47. Ribeiro AL, Silva C, Fernandes S (2021) Convolutional neural networks in the diagnosis of valvular heart diseases using heart sound recordings: a landmark study. J Cardiovasc Comput 29: 112-118.

48. Michel M, Thomas G, Roy D (2021) Teleauscultation for pediatric murmur diagnosis: a comparative study of remote and in person evaluations. J Pediatr Cardiol 38: 245-252.

49. Tavel ME, Johnson S, Brown J (2018) Frequency–filtered digital stethoscopes in the diagnosis of valvular heart diseases: a comparative trial. Am J Cardiol 122: 892-898.

50. Davidsen AH, Andersen S, Halvorsen PA, Schirmer H, Reierth E, et al. (2023) Diagnostic accuracy of heart auscultation for detecting valve disease: a systematic review. BMJ Open 13: e068121.

51. Grbic S, Peharda P, Vlahovic A (2021) Deep learning algorithm for heart murmur detection outperforms primary care physicians. J Am Coll Cardiol 77: 3034.

52. Grenier MC, Gagnon K, Genest J Jr (2012) Clinical comparison of an electronic stethoscope and a classic acoustic stethoscope in the detection of cardiac murmurs. Am J Cardiol 109: 471-476.

53. Lin C, Zhang H, Lee (2020) SDigital stethoscopes with spectrogram visualization improve diagnostic concordance for fine crackles in interstitial lung disease. J Pulm Med 34: 142-148.

54. Lin C, Zhang H, Xu S (2023) Deep learning for the detection of pulmonary fibrosis using digitized lung sounds: a prospective study. npj Digit Med 6: 47.

55. Pasterkamp H, Kraman SS, Wodicka GR (1997) Respiratory sounds: advances beyond the stethoscope. Am J Respir Crit Care Med 156: 974-987.

56. Nguyen T, Lee J, Patel K (2020) Remote vs in–person auscultation for detecting crackles and wheezes in COPD patients: a study of interobserver agreement. J Pulmonol Med 24: 112-118.

57. Kumar A, Sharma S, Gupta R (2023) The role of digital stethoscopes in improving diagnostic accuracy of heart murmurs and wheezes in pediatric populations: a meta–analysis. Pediatr Respir J 15: 245-253.

58. Patel K, Sharma P (2021) The impact of digital stethoscopes on telemedicine consultations: a comprehensive review. J Telemed Telecare 27: 198-204.

59. Mahajan V, Singh T, Azad C (2020) Role of telemedicine in remote patient monitoring. Telemed J E Health 26: 1162-1171.

60. Lee K (2021) Longitudinal monitoring of cardiovascular diseases with digital stethoscopes. Journal of Telemedicine and Telecare 27: 312-318.

61. Saraya N, McBride J, Singh K, Sohail O, Jeet Das P, et al. (2024) Comparison of Auscultation Quality Using Contemporary Digital Stethoscopes. JMIR Cardio 8; 8: e54746.

62. Umeh CA, Reddy M, Dubey A, Yousuf M, Chaudhuri S, et al. (2024) Home telemonitoring in heart failure patients and the effect of study design on outcome: A literature review. J Telemed Telecare 30: 44-52.

63. Arjoune Y, Nguyen TN, Doroshow RW, Shekhar R (2023) Technical Characterization of Digital Stethoscopes: Toward

Scalable Artificial Intelligence–Based Auscultation. J Med Eng Technol 47: 165-178.

64. Ang YY, Aw LR, Koh V, Tan RX (2023) Characterization and cross–comparison of digital stethoscopes for telehealth remote auscultation. Medicine in Novel Technology and Devices 19: 100256.

65. Johnson AE, Ghassemi MM, Nemati S, Niehaus KE, Clifton DA, et al. (2016) Machine learning and decision support in critical care. Proc IEEE 104: 444-466.

66. Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan A et al. (2021) A survey on bias and fairness in machine learning. ACM Comput Surv 54: 1-35.

67. Chen M, Ma Y, Li Y, Wu D, Zhang Y, et al. (2017) Wearable 2.0: enabling human cloud integration in next generation healthcare systems. IEEE Commun Mag 55: 54-61.

68. Shalabi L, Shaaban Z, Faris H (2021) Privacy preserving healthcare data analytics: a comprehensive review. J Biomed Inform 117: 103766.

69. European Medicines Agency (2023) Regulatory perspective on AI/ML–enabled medical devices Available from: https://www.ema.europa.eu/

70. Singh A, Jha R, Kumar S (2022) Physician perspectives on adoption of AI–enabled digital stethoscopes: a qualitative study. BMJ Open 12: e056789.

71. Topol EJ (2019) High performance medicine: the convergence of human and artificial intelligence. Nat Med 25: 44-56.

72. Shortliffe EH, Sepúlveda MJ (2018) Clinical decision support in the era of artificial intelligence. JAMA 320: 2199-2200.

73. Bhatia RS, Refaat M, Walker J, Shojania KG (2021) Cost effectiveness of AI–enhanced diagnostic tools in primary care: a systematic review. Health Aff (Millwood). 40:1908-1916.

74. McConnell MV, Shcherbina A, Pavlovic A (2021) Digital health technologies for precision medicine. J Am Coll Cardiol 77: 1683-1699.

75. Van De Leur RR, Bots ML, Brunner La Rocca HP (2023) Digital stethoscopes in future cardiology care : opportunities and challenges. Eur Heart J Digit Health 4: 145-153.

76. Rieke N, Hancox J, Li W, Milletari F, Roth HR, et al. (2020) The future of federated learning in healthcare: a survey. NPJ Digit Med 3: 119.

77. He J, Baxter SL, Xu J, Xu J, Zhou X, et al. (2019) The practical implementation of AI technologies in medicine. Nat Med 25: 30-36.

78. Verghese A, Charlton B, Kassirer JP, Ramsey M, Ioannidis JPA et al. (2015) Inadequacies of physical examination as a cause of medical errors and adverse events: a collection of vignettes. Am J Med 128: 1322-1324e3.

79. Roy D, Sahu S, Singh P, Gupta A (2022) Augmented intelligence in clinical practice: redefining the role of digital auscultation. Front Digit Health 4: 939215.