REVIEW ARTICLE

Digital Stethoscope Use in Neonates: A Systematic Review

Meagan Roff[1], Olivia Slifirski[1], Ethan Grooby[2,3], Faezeh Marzbanrad[2], Atul Malhotra[1,4]

Received on: 14 June 2023; *Accepted on:* 22 July 2023; *Published on:* 25 September 2023

Abstract

Aim: To assess the evidence for the use of digital stethoscopes in neonates and evaluate whether they are effective, appropriate, and advantageous for neonatal auscultation.

Methods: A systematic review and narrative synthesis of studies published between January 1, 1990 and May 29, 2023 was conducted following searches of MEDLINE, Embase, PubMed, Scopus, and Google Scholar databases, as well as trial registries.

Results: Of 3,852 records identified, a total of 41 papers were eligible and included in the narrative synthesis. Thirteen records were non-full-text articles, either in the form of journal letters or conference abstracts, and these were included separately for completion purposes but may be unreliable. Twenty eight papers were full-text articles and were included in a full qualitative analysis. Digital stethoscopes have been studied in neonatology across various clinical areas, including artificial intelligence for sound quality assessment and chest sound separation ($n = 5$), cardiovascular sounds ($n = 11$), respiratory sounds ($n = 4$), bowel sounds ($n = 4$), swallowing sounds ($n = 2$), and telemedicine ($n = 2$). This paper discusses the potential utility of digital stethoscope technology for the interpretation of neonatal sounds for both humans and artificial intelligence. The limitations of current devices are also assessed.

Conclusions: The utilization of digital stethoscopes in neonatology is an emerging field with a wide range of potential applications, which has the capacity to advance neonatal auscultation. Artificial intelligence and digital stethoscope technology offer novel objective avenues for automatic pathological sound detection. Further, digital stethoscopes may improve our scientific understanding of normal neonatal physiology and can be employed in telemedicine to facilitate remote medical access. Digital stethoscopes can also provide phonocardiograms, enabling enhanced interpretation of neonatal cardiac sounds. However, current digital stethoscopes necessitate refinement as they consistently produce low-quality sounds when used on neonates.

Keywords: Artificial Intelligence, Auscultation, Computer-assisted auscultation, Infant, Machine learning, Murmur detection, Newborn, Phonocardiography, Respiratory distress, Telemedicine.

Newborn (2023): 10.5005/jp-journals-11002-0068

Introduction

The stethoscope has been a crucial component of patient examination since its invention in 1816 by French physician, Laennec.[1] Over the past 200 years, it has undergone significant transformations and upgrades, with the standard device used by clinicians today being the dual-sided acoustic stethoscope.[1–3] However, there are several drawbacks of the acoustic stethoscope: interpretation is subjective and dependent on clinician expertise and hearing ability.[4–8] Furthermore, in neonates, even infant-sized acoustic stethoscopes can be unreliable and produce poor-quality sounds due to neonatal factors such as their small size, fast heart and respiratory rates, irregular breathing patterns, and noise interference (e.g., crying and respiratory support noise).[9–13] This can hinder accurate clinician analysis and may lead to delayed diagnosis and management of neonatal conditions (Fig. 1).

Technological advancements have led to the development of a digital (or electronic) stethoscope (DS), which offers solutions to the limitations seen in acoustic stethoscopes. Digital stethoscopes can amplify sounds, filter out unnecessary noises, and separate desired sounds. This improves sound focus and reduces reliance on hearing ability.[14,15] They also allow for the recording, playback, and sharing of sounds with other doctors for secondary opinions.[1,14,15] Furthermore, the integration of artificial intelligence (AI) into DS technology enables a more objective interpretation of auscultatory sounds.[16] For example, Eko Health's AI mobile application connects to DSs via Bluetooth, providing AI features such as heart rate estimation and murmur analysis (88% sensitivity and specificity for murmur detection).[17,18]

[1]Department of Paediatrics, Monash University, Melbourne, Australia

[2]Department of Electrical and Computer Systems Engineering, Monash University, Melbourne, Australia

[3]Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, British Columbia, Canada

[4]Monash Newborn, Monash Children's Hospital, Melbourne, Australia

Corresponding Author: Atul Malhotra, Department of Paediatrics, Monash University, Melbourne, Australia, Phone: +61 385723650, e-mail: atul.malhotra@monash.edu

How to cite this article: Roff M, Slifirski O, Grooby E, *et al*. Digital Stethoscope Use in Neonates: A Systematic Review. Newborn 2023; 2(3):235–243.

Source of support: Nil

Conflict of interest: None

Commercially available DSs designed for children and adults exist, but there is currently no specific DS designed for neonates.[19–24] A systematic review by Ramanathan et al. in 2018 concluded that further research was required to determine the advantages and disadvantages of current DSs for use in pediatrics.[25] Since then, several studies have assessed DSs exclusively in neonates, yet the suitability of DSs for use in this population remains uncertain. This systematic review aimed to evaluate the current evidence on DS use in neonates. Specifically, we assessed their utility, suitability, and limitations in neonatal areas such as the cardiovascular, respiratory, and gastrointestinal systems. Additionally, this review investigated the integration of DSs with AI for neonatal care.

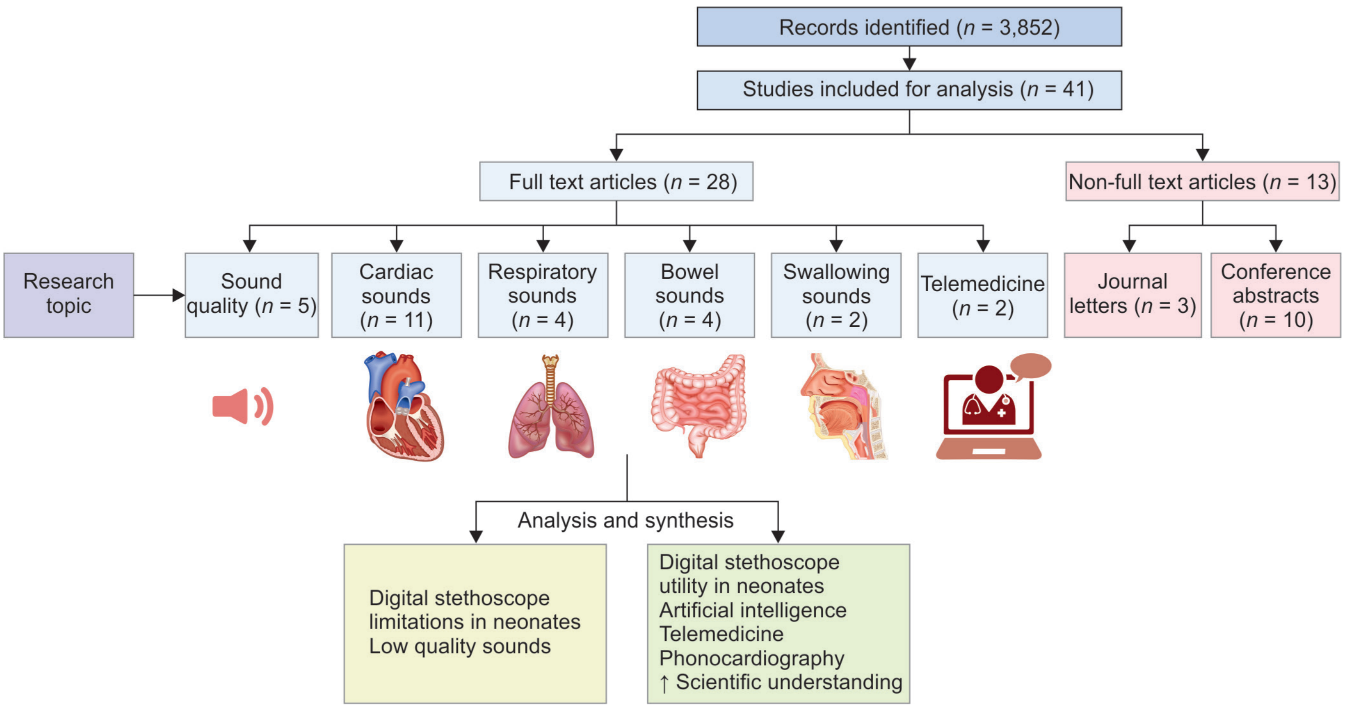

Fig. 1: Graphical abstract
Created with BioRender.com

Methods

A systematic review was performed to assess the utility of DSs in neonates. Digital stethoscopes were defined as any device that can record internal sounds via skin contact.

Inclusion criteria consisted of (1) involved neonates, (2) DS involvement, and (3) human studies. Exclusion criteria included (1) no subgroup analysis of neonatal population in studies with broader age range, (2) no DS involvement, (3) animal studies, (4) review articles or systematic reviews, and (5) non-English-accessible papers.

The databases searched included MEDLINE, Embase, PubMed, Scopus, and Google Scholar. Gray literature was searched for on clinical trial registries (WHO ICTRP, Clinicaltrials.gov, ANZCTR) and conference papers on Google Scholar. Relevant articles underwent backward and forward citation searching. The latest search was conducted on 29/05/2023.

The search strategy is provided in Table 1 of Supplementary File. MeSH, keywords, Boolean operators, synonyms, and truncations were used. The search was limited to English language articles published from January 1st, 1990 to present (DSs first discussed in 1990s).

Papers identified were uploaded onto the Covidence Systematic Review Software, which was used for screening and reviewing full-text papers for inclusion by two independent reviewers (MR and OS).[26] Duplicates were automatically removed, and conflicts were resolved by a third reviewer (AM).

Papers meeting inclusion criteria were included in a narrative synthesis. A narrative synthesis was deemed to be the most suitable approach to comprehensively synthesize findings due to the absence of randomized controlled trials and heterogeneity of studies, making a meta-analysis inappropriate. One author (MR) collected and synthesized the data, and two authors (AM and FM) reviewed it. Information sought from papers included: author, year, aim, number of participants, participant characteristics, DS device used, and main findings. Studies were categorized into six groups based on their study focus: AI for sound quality assessment and chest sound separation, cardiac sounds, respiratory sounds, bowel sounds, swallowing sounds, and telemedicine.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist for this systematic review is provided in Table 2 of Supplementary File.[27]

Results

A total of 3,852 records were identified through the search strategy, 41 records fulfilled the inclusion criteria. Figure 2 illustrates the PRISMA flow diagram for the systematic review.[27]

Twenty-eight full-text papers on DSs in neonates were identified, focusing on six clinical domains: AI for sound quality assessment and chest sound separation (n = 5), cardiac sounds (n = 11), respiratory sounds (n = 4), bowel sounds (n = 4), swallowing sounds (n = 2), and DS use in telemedicine (n = 2). Studies utilized DS devices originally designed for different age groups: adults (n = 11), children (n = 8), neonatal bowel sounds (n = 1), and unspecified (n = 8). Table 1 presents the full-text papers, and the evidence regarding DS use in the neonatal domains is discussed below.

Thirteen non-full-text papers, including journal letters (n = 3) and conference abstracts (n = 10), were identified. However, these papers may be unreliable due to incomplete reporting, publication bias, and some results may be preliminary findings. See Table 3 in Supplementary File for the non-full-text records.

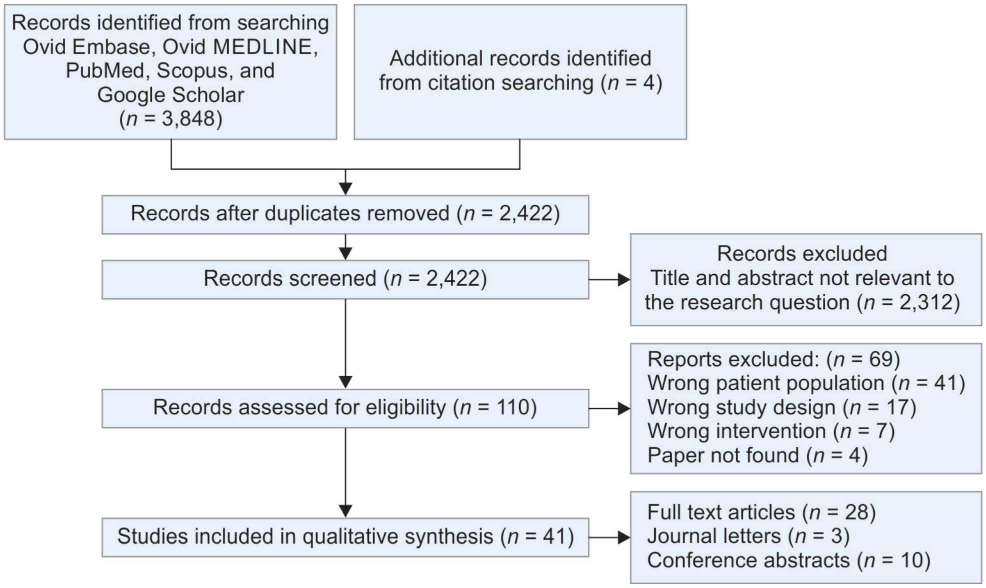

Fig. 2: PRISMA flow diagram for the systematic review of digital stethoscopes use in neonates. Adapted from the "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews"[27]

Table 1: Full-text published studies on digital stethoscope use in neonates

Author (year)	*Principal aim*	*Participant characteristics*	*Device used*	*Main findings*
AI for sound quality assessment and chest sound separation				
Grooby et al. (2021)[9]	Heart and lung sound quality assessment	Preterm/term neonates (2–48 hours old) *n* = 76	CliniCloud DS	The algorithm differentiated between high- and low-quality heart and lung sounds. Improved signal quality correlated with improved vital sign estimation.
Grooby et al. (2021)[28]	NMCF chest sound separation	Preterm/term neonates (2–48 hours old) *n* = 60	CliniCloud DS	NMCF algorithm outperformed existing methods in separating chest sounds.
Grooby et al. (2022)[10]	Real-time, multilevel heart and lung sound quality assessment	Preterm/term neonates (2–48 hours old) *n* = 119	CliniCloud DS	The method achieved real-time quality assessment of heart and lung sounds on a scale of 1–5.
Fattahi et al. (2022)[11]	SCBSS chest sound separation	Preterm/term neonates (24–48 hours old) *n* = 91	CliniCloud DS	SCBSS produced better-quality recordings and more accurate vital sign estimation compared with seven existing chest sound separation methods.
Grooby et al. (2023)[12]	NMCF and NMF chest sound separation	Extremely preterm-to-term neonates (2 hours–60 days old) *n* = 213	CliniCloud DS	NMCF and NMF systems outperformed the best existing methods in separating chest sounds.
Cardiac sounds				
Yang and Zeng (2010)[29]	PCG to evaluate cardiac reserve	Preterm/term neonates (unspecified age) *n* = 385	PCG sensor	PCG cardiac indicators were higher in term neonates than preterm neonates, correlating with increased cardiac reserve.

(Contd...)

Table 1: *(Contd....)*

Author (year)	*Principal aim*	*Participant characteristics*	*Device used*	*Main findings*
Balogh and Kovács (2011)[30]	AI neonatal PCG PDA closure classification	Preterm neonates (average age of 6 days) *n* = 25	Self-made DS (electret microphone capsule)	Characteristic heart sound calculation method showed favorable results for the identification of PDAs.
Sung et al. (2013)[31]	Temporal correlogram method to analyze PDA murmur before and after transcatheter closure	PDA neonates (unspecified age) *n* = 2	3M Littmann 3200 DS	Cochlear spectrogram and temporal correlogram show distinct differences in neonatal heart sounds following PDA transcatheter closure.
Amiri et al. (2017)[32]	AI neonatal PCG murmur classification	Neonates with/without heart murmurs (1–20 days old) *n* = 116	DS (unspecified)	Classified PCG heart recordings as normal or pathological with an AUC of 0.98.
Shelevytska and Mavropulo (2018)[33]	PCG analysis of hemodynamic disorders in preterm neonates	Preterm NICU neonates with/without PDA (median day 5 of life) *n* = 45	ThinkLabs ds32a	Differences observed in computer analyzed PCG recordings between hemodynamically stable and unstable preterm neonates.
Grgic-Mustafic et al. (2019)[34]	AI neonatal PCG murmur classification	NICU neonates, both preterm and term, with or without heart murmurs (1–5 days old) *n* = 36	3M Littmann 3200 DS	Developed PCG classification demonstrated higher sensitivity and comparable specificity to pediatrician auscultation in distinguishing between normal and pathological heart sounds.
Bobillo-Perez et al. (2021)[35]	Comparison of devices for HR estimation at birth	Healthy-term newborns (at birth) *n* = 50	3M Littmann 3200 DS	Ultrasound detected HR fastest, followed by DS, ECG, and pulse oximetry.
Gómez-Quintana et al. (2021)[36]	AI neonatal PCG segmentation	Healthy, PDA, and CHD neonates (0–6 days old) *n* = 265	ThinkLabs ds32a and ThinkLabs One DS	Developed PCG segmentation method outperformed previously designed adult-based version.
Gómez-Quintana et al. (2021)[37]	AI neonatal PCG PDA detection	Healthy, PDA and CHD neonates (0–6 days old) *n* = 265	ThinkLabs ds32a and ThinkLabs One DS	Developed method reached an AUC of 77% and 78% for the detection of PDA and CHD, respectively, outperforming human listeners.
Takahashi et al. (2021)[38]	Piezoelectric sensor vs. electronic stethoscope in neonatal heart murmur detection	Neonates with/without systolic heart murmurs caused by CHD (1–26 days old) *n* = 18	3M Littmann 3200 DS and self-made piezoelectric sensor	Piezoelectric sensor performed marginally lower than the DS in detecting systolic murmurs.
Amiri et al. (2022)[39]	AI neonatal PCG heart disease classification	Neonates with/without heart murmurs (1–20 days old) *n* = 120	DS (unspecified)	Detected heart disease with 96.15% sensitivity and 91.67% specificity.
Respiratory sounds				
Blowes et al. (1995)[40]	Neonatal lung sound interpretation with and without added dead space	Term neonates (12 hours–6 days old) *n* = 16	Small piezoelectric accelerometer	Added dead space increased lung sound intensity but had no uniform influence on lung sound frequency.

Ramanathan et al. (2020)[41]	Lung sound changes in transitioning newborns	Term neonates (at 1 minute and 2 hours of life) $n = 61$	CliniCloud DS	Lung sound frequencies decreased over the first 2 hours of life; neonates who developed RD had higher frequencies at birth.
Zhou et al. (2020)[42]	Lung sound characteristics in preterm and term neonates	Preterm/term neonates without respiratory support (24–48 hours old) $n = 52$	CliniCloud DS	Preterm and term newborns had different lung sound features.
Grooby et al. (2022)[43]	AI to predict the development of RD at birth before symptom onset	Term neonates, 9 later developed RD (at 1 minute of life, clinical condition tracked for the first few hours) $n = 51$	CliniCloud DS	Algorithm predicted neonatal RD with a 66.7% sensitivity and 85% specificity in combined chest recordings.
Bowel sounds				
Song et al. (2021)[44]	AI bowel sound detection and classification	NICU neonates (unspecified age) $n = 113$	BoSS (microelectronic stethoscope)	Classified bowel sounds into short (91% sensitivity, 71% specificity) and long bursts (97% sensitivity, 72% specificity).
Sitaula et al. (2022)[45]	AI bowel sound detection	NICU neonates (unspecified age) $n = 49$	3M Littmann 3200 DS	Identified bowel sounds with an AUC 83.96%, outperforming the next-best method by 3%.
Burne et al. (2022)[46]	AI bowel sound detection	NICU neonates (unspecified age) $n = 49$	3M Littmann 3200 DS	Identified bowel sounds with an AUC 85.6%.
Zhou et al. (2022)[47]	Feasibility of long continuous bowel sound recordings and AI analysis	Stable term neonates with/without mild–moderate hyperbilirubinemia (4.51 ± 5.34 days old) $n = 82$	MEMS sensor	Recordings made for 20 hours. AI analysis measured five bowel sound characteristics that were unaffected by hyperbilirubinemia but influenced by intake of mother's breast milk.
Swallowing sounds				
Da Nobrega et al. (2004)[48]	Assessing swallowing pattern for feeding maturation in newborns	Preterm neonates (37.8 ± 1.5 weeks postmenstrual age) $n = 23$	Small microphone	Swallowing time and bursts increased during transition from tube bottle feeding to bottle feeding.
Ince et al. (2014)[49]	Assessing feeding maturation in newborns	Preterm/term neonates (regular follow-up until 40 weeks postmenstrual age) $n = 94$	ThinkLabs ds32a	Volume of milk ingested and number of rhymical swallows increased with gestational age.
Telemedicine				
Garingo et al. (2012)[50]	NICU robotic telemedicine compared with in-person consults	Preterm/term NICU neonates (3–112 days old) $n = 46$	DS (unspecified)	NICU telemedicine is feasible. Disagreements between in-person acoustic stethoscope and telemedicine DS interpretation.
Umoren et al. (2020)[51]	Feasibility of in-hospital telemedicine for infection control	NICU neonates in strict isolation due to infection (unspecified age) $n = 3$	3M Littmann 3200 DS	Threefold reduction in potential exposures between neonates and healthcare workers using in-hospital telemedicine.

AI, artificial intelligence; AUC, area under curve; BoSS, bowel sounds sensor; CHD, congenital heart disease; DS, digital stethoscope; ECG, electrocardiogram; HR, heart rate; MEMS sensor, microelectromechanical system sensor; NICU, neonatal intensive care unit; NMCF, non-negative matrix co-factorization; NMF, non-negative matrix factorization; PDA, patent ductus arteriosus; PCG, phonocardiogram; RD, respiratory distress; RR, respiratory rate; SCBSS, single-channel blind source separation

AI for Sound Quality Assessment and Chest Sound Separation

Robust AI sound analysis software requires reliable algorithms trained on large datasets, with high-quality data that correspond with future input requirements.[52,53] Five papers in this review focused on developing AI methods to enhance overall sound quality and improve the accuracy of future AI classification systems.[9–12,28]

Two papers developed algorithms to distinguish between low- and high-quality recordings.[9,10] High-quality recordings yielded significantly more accurate estimations of heart and breathing rates compared with low-quality recordings.[9] In their 2021 software, Grooby et al. achieved 82% accuracy (69% sensitivity and 86% specificity) in differentiating low- and high-quality lung sounds and 93% accuracy (81% sensitivity and 86% specificity) for heart sounds.[9] Furthermore, Grooby et al.'s 2022 paper introduced multilevel and real-time quality features.[10] Incorporating this software into DS technology could provide real-time quality assessment during auscultation, eliminating the need for retrospective analysis of recordings. However, further refinement is necessary as the algorithm's accuracy was relatively low, possibly due to annotator disagreement when scoring recordings on a scale of 1–5 rather than categorizing them as low- or high-quality.[10]

Auscultation in newborns is challenging for both humans and AI due to the presence of a mixture of different sounds (e.g., cardiac, respiratory, gastrointestinal, crying, and environment noises). Three papers developed chest sound separation programs to isolate cardiac, respiratory, and other sounds.[11,12,28] These papers examined three sound separation methods: non-negative matrix co-factorization, non-negative matrix factorization, and single-channel blind source separation. Using the aforementioned sound quality assessment tools, they evaluated the quality of cardiac and respiratory sounds after separation and all three papers demonstrated improved signal quality compared with previous approaches.[11,12,28] However, complete separation of chest sounds remained challenging, particularly in neonates on respiratory support. This was due to overlapping frequencies between sounds of interest and the impurity of training mixtures.[11,12,28] Using higher-quality recordings for software training could potentially address this issue.[11,12,28]

These algorithms improve the overall quality, focus, and clarity of DS-recorded neonatal sounds.[9–12,28] This software can be integrated into DS technology to enhance human interpretation and the accuracy of future AI programs.

Cardiac Sounds

Eight cardiac studies utilized the phonocardiogram (PCG) component of DS technology to analyze neonatal heart sounds, revealing additional features beyond auscultation alone. Phonocardiograms can enhance neonatal heart sound interpretation by detecting decreased cardiac reserve, hemodynamic disorders, and with the assistance of AI, heart sounds can be segmented, and murmurs automatically detected.[29,30,32–34,37,39]

Artificial intelligence murmur detection programs can indicate the presence of neonatal murmurs and classify them as either innocent or pathological.[30,32,34,37,39] Additionally, specific PCG features have been identified for murmurs related to patent ductus arteriosus, leading to the development of AI detection program specifically for this common neonatal condition.[30,37] Eventually, this software could be widely used to screen newborns for the early detection of cardiac murmurs. However, software refinement is needed due to limitations in accuracy arising from small datasets and low-quality recordings.[30,32,34,36,37,39]

Respiratory Sounds

Digital stethoscope recorded breath sound analysis reveals differences in lung sound characteristics between preterm and term newborns.[42] Power spectra analysis demonstrates that term newborns exhibit higher power in the middle- and high-frequency range, while preterm newborns have higher power in the very-high-frequency range.[42] These differences may be attributed to the smaller size and underdeveloped lungs of preterm newborns. Further research is needed to explore the clinical implications of these findings, including their potential impact on AI detection methods.[42]

During the newborn transition period, DS technology observes a decrease in lung sound frequency over the first 2 hours of life.[41] Newborns who develop respiratory distress (RD) show higher frequencies from birth, suggesting a correlation with decreased fluid clearance.[41] Grooby et al. developed an AI program based on these findings to predict RD at birth before symptom onset.[43] When combining anterior and posterior recordings and utilizing both heart and lung sounds, the program achieved an overall accuracy of 81.8% (66.7% sensitivity and 85% specificity) for predicting RD, thus demonstrating the potential of DS AI for early detection and management of neonatal conditions.[43]

However, these studies are limited by low-quality recordings and small datasets.

Bowel Sounds

AI models, including Hidden Semi-Markov and Convolutional Neural Network models, have been used to detect and locate neonatal bowel sounds (including peristalsis) in DS recordings that contain mixtures of sounds.[45,46] These studies detected bowel sounds with an area under the curve of 83.96% and 85.6%, respectively, outperforming previous AI methods. The detection and localization of bowel sounds may improve clinician interpretation and the accuracy of AI-based bowel sound characterization and classification methods.[45,46]

Artificial intelligence has enabled the successful extraction of bowel sound characteristics, providing additional parameters beyond what can be measured with an acoustic stethoscope.[44,47] However, further research is necessary to determine the clinical significance of these characteristics in normal and pathological neonatal bowel activity before these programs can be utilized in a clinical setting.[44,47]

Overall, integrating bowel sound detection and characterization methods into future classification models holds promise in enhancing the timely diagnosis of neonatal bowel conditions. Nonetheless, these studies are limited by low-quality recordings, which may impact AI accuracy.[44–47]

Swallowing Sounds

Feeding difficulties in premature neonates pose challenges in timing the advancement of feeding methods.[48,49] Digital stethoscope studies indicate that feeding maturation is associated with increased swallowing features, which correlate with gestational age.[48,49] Accordingly, DS technology can assess swallowing sounds and guide feeding strategies for neonates experiencing swallowing difficulties.

Telemedicine

Digital stethoscopes in neonatal telemedicine have been studied for infection control within neonatal intensive care units.[50,51] Garingo et al. observed the differences between telemedicine DS and in-person acoustic stethoscope findings, as well as variations in the results among multiple neonatologists using the acoustic stethoscope on the same newborn.[50] This suggests observer interpretation variability rather than DS error, and raises the concern of stethoscope interpretation subjectivity that can affect clinical decision-making.[4,50] Additionally, neonatal intensive care unit telemedicine can reduce infection exposure by threefold, aiding in infection control and minimizing the use of personal protective equipment in resource-limited settings.[51]

Neonatal telemedicine should be explored further and may also facilitate remote access in areas with pediatric specialist shortages and promote collaboration between specialists.[50,51]

Discussion

Digital stethoscopes show promise in enhancing the analysis of neonatal cardiac, respiratory, and gastrointestinal sounds. A key advantage lies in the integration of AI within DS technology, enabling the improved acquisition of clear neonatal sounds and the automatic detection, characterization, and classification of neonatal sounds.[9–12,28,30,32,34,36,37,39,43–47] This surpasses the capabilities of traditional acoustic stethoscopes and eliminates listener subjectivity. In the reviewed studies, DS AI was used to improve sound quality, isolate sounds of interest, estimate vital signs, segment PCG heart sounds, and detect indicators of pathological conditions (e.g., murmurs, RD).[9–12,28,30,32,34,36,37,39,43–47] These findings lay the groundwork for a plethora of possible AI tools and opportunities that could be developed to further advance automatic neonatal sound analysis. Such advancements have the potential to improve the timeliness of diagnosis and management for various neonatal medical conditions. Digital stethoscopes offer other benefits, including their application in neonatal telemedicine for infection control, their potential to enhance our scientific understanding of neonatal physiology, and the utilization of PCGs to capture additional cardiac features.[29,30,32–34,36,37,39,41,42,48–51]

Several limitations in the literature impacted the accuracy and reliability of findings, thereby hindering the clinical application of DSs in neonates. Major limitations included small sample sizes, findings with an unclear clinical relevance, and low-quality recordings. Small sample sizes have limited the reliability and generalizability of results. Furthermore, the clinical utility of these findings is hindered by a knowledge gap concerning the correlation between sound characteristics and different neonatal conditions, as well as factors such as gestational age, postnatal age, and size. Bridging these gaps through novel studies is required to facilitate the translation of these findings into clinical practice and to advance AI classification programs. Additionally, a consistent issue identified throughout the reviewed articles was the production of low-quality DS sounds, which reduced human and AI sound interpretation accuracy. This was a particular issue in AI-focused studies; low-quality sounds were either used to train AI algorithms, reducing overall data quality, or they were removed, reducing data quantity. Both options decreased the accuracy of the developed AI methods, thereby reducing program reliability.

Low-quality DS sounds raise concerns about the suitability of current DSs for neonatal use, as they may not adequately account for neonatal factors, and this can be detrimental to accurate clinician and AI analysis. It is worth noting that many devices used in the reviewed studies were devices originally designed for children ($n = 8$), adults ($n = 11$), or unspecified $n = 8$), rather than specifically for neonates.[9–12,28–43,45–51] While sound quality assessment and sound separation AI programs can help isolate high-quality sounds, they have limitations and do not address the issue of having low-quality sounds in the first place.[9–12,28] Alternatively, a DS specifically designed for neonates could be a viable solution to improve the device's capacity in producing high-quality neonatal sounds. Ultimately, a device capable of capturing high-quality neonatal sounds has the potential to enhance clinician interpretation and AI accuracy and capability for the improved diagnosis and management of neonatal medical conditions.

Regarding the limitations of this systematic review, although efforts were made to ensure a comprehensive search strategy, it is possible that not every relevant paper was identified, introducing potential selection bias. Additionally, the included studies exhibited heterogeneity, making it challenging to draw definitive conclusions regarding the suitability of DSs in neonates. Finally, the non-full-text articles in supplementary file may be lower quality and subject to publication and reporting bias.

Conclusions

Digital stethoscopes show promise in improving neonatal cardiovascular, respiratory, and gastrointestinal auscultation. The integration of DS technology with AI may facilitate the early diagnosis and management of neonatal conditions. However, current DS devices do not appear to be appropriate for neonates due to the production of low-quality sounds.

Supplementary Materials

All the Supplementary Tables are available online on the website of https://www.newbornjournal.org/.

References

1. Permin H, Norn S. Stethoscope – Over 200 years. J Pulmonol Respir Res 2019;3:001–008. DOI: 10.29328/journal.jprr.1001010.
2. Harbison J. 'The old guessing tube': 200 years of the stethoscope. QJM: An Int J Med 2017;110(1):9–10. DOI: 10.1093/qjmed/hcw108.
3. 3M Littmann. 3M Littmann Classic II Infant Stethoscope [cited 2023 March 28]. Available from: https://www.littmann.com.au/3M/en_AU/littmann-stethoscopes-au/products/~/3M-Littmann-Classic-II-Infant-Stethoscope/?N=5932256+8711017+3290700351+3294857444&rt=rud.
4. Hafke-Dys H, Bręborowicz A, Kleka P, et al. The accuracy of lung auscultation in the practice of physicians and medical students. PLoS One 2019;14(8):e0220606. DOI: 10.1371/journal.pone.0220606.
5. Bank I, Vliegen HW, Bruschke AV. The 200th anniversary of the stethoscope: Can this low-tech device survive in the high-tech 21st century? Eur Heart J 2016;37(47):3536–3543. DOI: 10.1093/eurheartj/ehw034.
6. Richardson TR, Moody JM. Bedside cardiac examination: Constancy in a sea of change. Curr Probl Cardiol 2000;25(11):783–825. DOI: 10.1067/mcd.2000.109835.
7. Zun LS, Downey L. The effect of noise in the emergency department. Acad Emerg Med 2005;12(7):663–666. DOI: 10.1197/j.aem.2005.03.533.
8. Arts L, Lim EHT, van de Ven PM, et al. The diagnostic accuracy of lung auscultation in adult patients with acute pulmonary pathologies: A meta-analysis. Sci Rep 2020;10(1):7347. DOI: 10.1038/s41598-020-64405-6.
9. Grooby E, He J, Kiewsky J, et al. Neonatal heart and lung sound quality assessment for robust heart and breathing rate estimation

for telehealth applications. IEEE J Biomed Health Inform 2021;25(12): 4255–4266. DOI: 10.1109/JBHI.2020.3047602.
10. Grooby E, Sitaula C, Fattahi D, et al. Real-time multi-level neonatal heart and lung sound quality assessment for telehealth applications. IEEE Access 2022;10:10934–10948. DOI: 10.1109/ACCESS.2022.3144355.
11. Fattahi D, Sameni R, Grooby E, et al. A blind filtering framework for noisy neonatal chest sounds. IEEE Access 2022;10:50715–50727. DOI: 10.1109/ACCESS.2022.3170052.
12. Grooby E, Sitaula C, Fattahi D, et al. Noisy neonatal chest sound separation for high-quality heart and lung sounds. IEEE J Biomed Health Inform 2023;27(6):2635–2646. DOI: 10.1109/JBHI.2022.3215995.
13. Elphick HE, Lancaster GA, Solis A, et al. Validity and reliability of acoustic analysis of respiratory sounds in infants. Arch Dis Child 2004;89(11):1059–1063. DOI: 10.1136/adc.2003.046458.
14. Swarup S, Makaryus AN. Digital stethoscope: Technology update. Med Devices (Auckl) 2018;11:29–36. DOI: 10.2147/MDER.S135882.
15. Tavel ME. Cardiac auscultation: A glorious past--and it does have a future! Circulation 2006;113(9):1255–1259. DOI: 10.1161/CIRCULATIONAHA.105.591149.
16. Ghanayim T, Lupu L, Naveh S, et al. Artificial intelligence-based stethoscope for the diagnosis of aortic stenosis. Am J Med 2022;135(9):1124–1133. DOI: 10.1016/j.amjmed.2022.04.032.
17. Eko Health Inc. Eko AI Validation White Paper; 2020 [cited 2023 March 29]. Available from: https://uploads-ssl.webflow.com/5fca50c07c4b1314fe246a86/6247c228d81d9f7823c752c1_Eko%20AI%20White%20Paper%20-%20LBL105B.pdf.
18. Eko Health Inc. Eko App [cited 2023 March 29]. Available from: https://www.ekohealth.com/pages/smart-stethoscope-app.
19. 3M Littmann. 3M Littmann CORE Digital Stethoscope [cited 2023 March 29]. Available from: https://www.littmann.com/3M/en_US/littmann-stethoscopes/advantages/core-digital-stethoscope/.
20. 3M Littmann. 3M Littmann Electronic Stethoscope Model 3200 [cited 2023 March 29]. Available from: https://www.littmann.com.au/3M/en_AU/littmann-stethoscopes-au/products/~/3M-Littmann-Electronic-Stethoscope-Model-3200/?N=5142935+8711017+3290263838+3294857444&preselect=5002684+3293786499&rt=rud.
21. Design and Industry. CliniCloud Digital Stethoscope [cited 2023 March 29]. Available from: https://www.design-industry.com.au/clinicloud.
22. Eko Health Inc. Eko DUO ECG + Digital Stethoscope [cited 2023 March 29]. Available from: https://www.ekohealth.com/products/duo-ecg-digital-stethoscope?variant=39350415655008.
23. Eko Health Inc. Eko CORE Digital Attachment [cited 2023 March 29]. Available from: https://www.ekohealth.com/products/core-digital-attachment?variant=32764121251936.
24. Thinklabs. Thinklabs One Digital Stethoscope [cited 2023 March 29]. Available from: https://www.thinklabs.com/.
25. Ramanathan A, Zhou L, Marzbanrad F, et al. Digital stethoscopes in paediatric medicine. Acta Paediatr 2019;108(5):814–822. DOI: 10.1111/apa.14686.
26. Covidence Systematic Review Software. Veritas Health Innovation, Melbourne, Australia. Available from: www.covidence.org.
27. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ 2021;372:n71. DOI: 10.1136/bmj.n71.
28. Grooby E, He J, Fattahi D, et al. A new non-negative matrix co-factorisation approach for noisy neonatal chest sound separation. Annu Int Conf IEEE Eng Med Biol Soc 2021:5668–5673. DOI: 10.1109/EMBC46164.2021.9630256.
29. Yang X, Zeng W. A relative value method for measuring and evaluating neonatal cardiac reserve. Indian J Pediatr 2010;77(6):661–664. DOI: 10.1007/s12098-010-0058-5.
30. Balogh ÁTK, Kovács F. Application of phonocardiography on preterm infants with patent ductus arteriosus. Biomed Sign Process Control 2011;6(4):337–345. DOI: 10.1016/j.bspc.2011.05.009.
31. Sung P-H, Wang J-N, Chen B-W, et al. Auditory-inspired heart sound temporal analysis for patent ductus arteriosus. In: 2013 1st International Conference on Orange Technologies (ICOT) 2013. pp. 231–234.
32. Amiri AM, Abtahi M, Constant N, et al. Mobile phonocardiogram diagnosis in newborns using support vector machine. Healthcare (Basel) 2017;5(1):16. DOI: 10.3390/healthcare5010016.
33. Shelevytska VA, Mavropulo TK. Computer-aided auscultation of hemodynamic disorders in preterm neonates. S WorldJournal 2018:22–27. DOI: 10.30888/2663-5712.2020-06-02-052.
34. Grgic-Mustafic R, Baik-Schneditz N, Schwaberger B, et al. Novel algorithm to screen for heart murmurs using computer-aided auscultation in neonates: A prospective single center pilot observational study. Minerva Pediatr 2019;71(3):221–228. DOI: 10.23736/S0026-4946.18.04974-5.
35. Bobillo-Perez S, Balaguer M, Jordan I, et al. Delivery room ultrasound study to assess heart rate in newborns: DELIROUS study. Eur J Pediatr 2021;180(3):783–790. DOI: 10.1007/s00431-020-03776-4.
36. Gomez-Quintana S, Shelevytsky I, Shelevytska V, et al. Automatic segmentation for neonatal phonocardiogram. Annu Int Conf IEEE Eng Med Biol Soc 2021:135–138. DOI: 10.1109/EMBC46164.2021.9630574.
37. Gómez-Quintana S, Schwarz CE, Shelevytsky I, et al. A Framework for AI-assisted detection of patent ductus arteriosus from neonatal phonocardiogram. Healthcare (Basel) 2021;9(2):169. DOI: 10.3390/healthcare9020169.
38. Takahashi K, Ono K, Arai H, et al. Detection of pathologic heart murmurs using a piezoelectric sensor. Sensors (Basel) 2021;21(4):1376. DOI: 10.3390/s21041376.
39. Amiri A, Armano G, Ghasemi S. Neonatal heart disease screening using an ensemble of decision trees. Int J Biomed Eng Technol 2022;39(2):107–130. DOI: 10.1504/IJBET.2022.124014.
40. Blowes RW, Yiallouros P, Milner AD. Lung sounds in neonates with and without an added dead space. Pediatr Pulmonol 1995;19(6):348–354. DOI: 10.1002/ppul.1950190607.
41. Ramanathan A, Marzbanrad F, Tan K, et al. Assessment of breath sounds at birth using digital stethoscope technology. Eur J Pediatr 2020;179(5):781–789. DOI: 10.1007/s00431-019-03565-8.
42. Zhou L, Marzbanrad F, Ramanathan A, et al. Acoustic analysis of neonatal breath sounds using digital stethoscope technology. Pediatr Pulmonol 2020;55(3):624–630. DOI: 10.1002/ppul.24633.
43. Grooby E, Sitaula C, Tan K, et al. Prediction of neonatal respiratory distress in term babies at birth from digital stethoscope recorded chest sounds. Annu Int Conf IEEE Eng Med Biol Soc 2022;2022: 4996–4999. DOI: 10.1109/EMBC48229.2022.9871449.
44. Song I, Huang Y, Koh THHG, et al. Pervasive monitoring of gastro-intestinal health of newborn babies. In: Pham DN, Theeramunkong T, Governatori G, eds. PRICAI 2021: Trends in Artificial Intelligence. Springer, Cham; 2021, vol. 13031. pp. 359–369.
45. Sitaula C, He J, Priyadarshi A, et al. Neonatal bowel sound detection using convolutional neural network and laplace hidden semi-Markov model. IEEE/ACM Trans Audio, Speech, Lang Process 2022;30: 1853–1864. DOI: 10.1109/TASLP.2022.3178225.
46. Burne L, Sitaula C, Priyadarshi A, et al. Ensemble approach on deep and handcrafted features for neonatal bowel sound detection. IEEE J Biomed Health Inform 2022;27(6):2603–2613. DOI: 10.1109/JBHI.2022.3217559.
47. Zhou P, Lu M, Chen P, et al. Feasibility and basic acoustic characteristics of intelligent long-term bowel sound analysis in term neonates. Front Pediatr 2022;10:1000395. DOI: 10.3389/fped.2022.1000395.
48. Da Nobrega L, Boiron M, Henrot A, et al. Acoustic study of swallowing behaviour in premature infants during tube-bottle feeding and bottle feeding period. Early Hum Dev 2004;78(1):53–60. DOI: 10.1016/j.earlhumdev.2004.03.008.
49. Ince DA, Ecevit A, Acar BO, et al. Noninvasive evaluation of swallowing sound is an effective way of diagnosing feeding maturation in newborn infants. Acta Paediatr 2014;103(8):e340–e348. DOI: 10.1111/apa.12686.
50. Garingo A, Friedlich P, Tesoriero L, et al. The use of mobile robotic telemedicine technology in the neonatal intensive care unit. J Perinatol 2012;32(1):55–63. DOI: 10.1038/jp.2011.72.

51. Umoren RA, Gray MM, Handley S, et al. In-hospital telehealth supports care for neonatal patients in strict isolation. Am J Perinatol 2020;37(8):857–860. DOI: 10.1055/s-0040-1709687.
52. Stowell D. Computational bioacoustics with deep learning: A review and roadmap. PeerJ 2022;10:e13152. DOI: 10.7717/peerj.13152.
53. Xu Y, Liu X, Cao X, et al. Artificial intelligence: A powerful paradigm for scientific research. Innovation (Camb) 2021;2(4):100179. DOI: 10.1016/j.xinn.2021.100179.