Review

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Posted Date: 14 May 2024

doi: 10.20944/preprints202405.0889.v1

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Review

Voice as a Biomarker of Pediatric Health: A Scoping Review

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Abstract: The human voice has the potential to serve as a valuable biomarker for the early detection, diagnosis, and monitoring of pediatric conditions. This scoping review synthesizes the current knowledge on the application of Artificial Intelligence (AI) in analyzing pediatric voice as a biomarker for health. The included studies featured voice recordings from pediatric populations aged 0-17 years, utilized feature extraction methods, and analyzed pathological biomarkers using AI models. Data from 62 studies were extracted, encompassing study and participant characteristics, recording sources, feature extraction methods, and AI models. The review showed a global representation of pediatric voice studies, with a focus on developmental, respiratory, speech, and language conditions. The most frequently studied conditions were Autism Spectrum Disorder, intellectual disabilities, asphyxia, and asthma. Mel-Frequency Cepstral Coefficients were the most utilized feature extraction method, while Support Vector Machines were the predominant AI model. The analysis of pediatric voice using AI demonstrates promise as a non-invasive, cost-effective biomarker for a broad spectrum of pediatric conditions. However, further research and development are crucial to enhance the accuracy and applicability of these tools in clinical settings.

Keywords: artificial intelligence; machine learning; pediatric health; vocal biomarkers

1. Introduction

The human voice is often referred to as a unique print for each individual. It contains biomarkers that have been linked in the adult literature to various diseases ranging from Parkinson's disease [66] to dementia, mood disorders, and cancers [64,65,67]. The voice contains complex acoustic markers that depend on respiration, phonation, articulation, and prosody coordination. Recent advances in acoustic analysis technology, especially when coupled with machine learning, have shed new insights into the detection of diseases. As a biomarker, the voice is cost-effective, easy, and safe to collect in low-resource settings. Moreover, the human voice contains not only speech, but other acoustic biomarkers such as cry, cough, and other respiratory sounds. The objective of this scoping review is to synthesize existing knowledge on the application of Artificial Intelligence (AI) in the analysis of pediatric voice as a biomarker for health to foster a deeper understanding of its potential use as an investigative or diagnostic tool within the pediatric clinical setting.

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2. Materials Methods

2.1. Registration and Funding

This scoping review was registered with the Open Science Framework (OSF) to enhance transparency and reproducibility. The review was registered on July 24, 2023 under the OSF registration DOI 10.17605/OSF.IO/SC6MG. The full registration details, including the review protocol and objectives can be accessed at https://osf.io/sc6mg. All phases of this study were supported by National Institutes of Health grant number: 1OT20D032720-01.

2.2. Search Strategy

Precise searches were conducted to identify relevant keywords and controlled vocabulary for the following concepts: artificial intelligence, voice, pediatrics, and disorders. Controlled vocabulary terms were combined logically by a medical librarian using Boolean logic, with keywords searched in the title and abstract to form a sensitive search strategy. The final search strategy utilized 217 keywords, including 91 related to "artificial intelligence," 45 related to "voice," 20 related to "pediatric," and 61 related to "disorder," as shown in Appendix I. The original PubMed search was translated into the following databases: Embase, Web of Science Core Collection, and the Cochrane database. Google Scholar and ClinicalTrials.gov were searched in order to pull in grey literature. All searches were run in May 2023 and deduplicated in EndNote using the validated deduplication method put forth by Bramer et al. [13]. Results were imported into Covidence, a systematic review software. Titles and abstracts were independently reviewed by two reviewers against pre-defined inclusion criteria. Relevant texts were moved to the full-text review, whereby the same process evaluated PDFs of eligible citations. Conflicting votes were resolved via discussion until the two original reviewers reached a consensus. The PRISMA flow chart of article inclusion is shown in Figure 1.

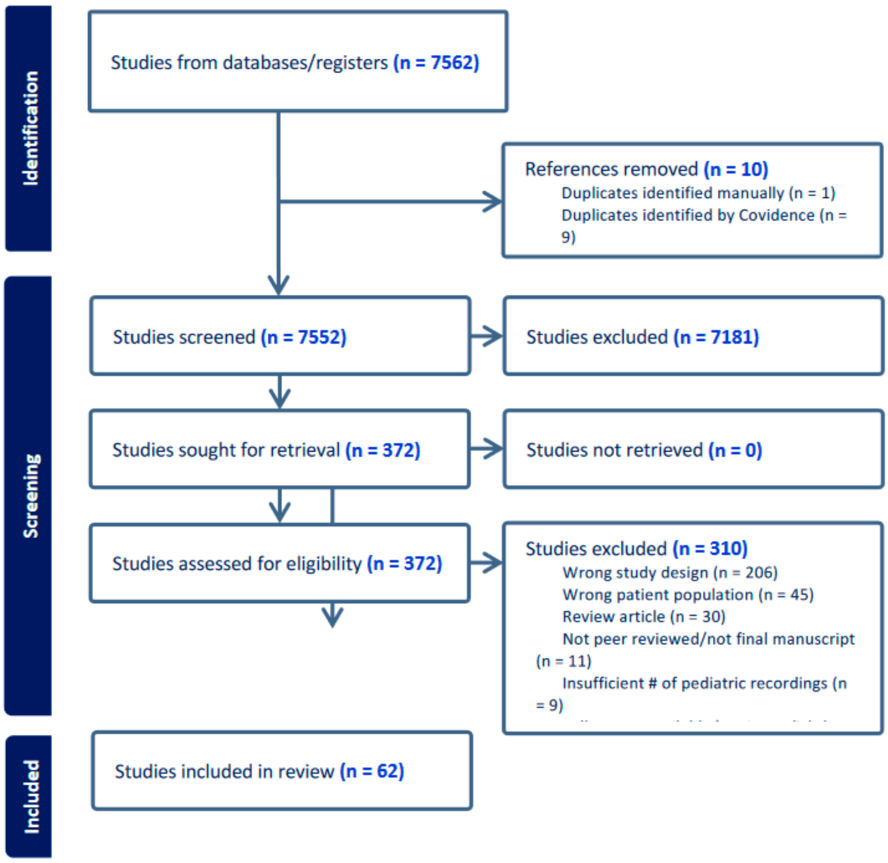

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Figure 1. PRISMA Flow Diagram of study inclusion from study identification, screening, and final inclusion.

2.3. Inclusion Criteria

Each study was required to include voice recordings in pediatric populations aged 0-17 years. Studies involving both pediatric and adult cohorts were considered on the basis that pediatric data were collected and analyzed separately from adult data. A minimum of 10 pediatric participants were required in each study. All pediatric health conditions were considered except for newborn or infant cry to detect hunger, discomfort, pain, or sleepiness. Studies were limited to peer-reviewed prospective or retrospective research studies written originally in English and excluded scoping reviews, literature reviews, and meta-analyses. Studies were required to utilize one or more feature extraction methods to produce a vocal dataset and required an analysis of pathological biomarkers contained in voice, cry, or respiratory sounds using one or more machine learning or artificial intelligence models.

2.4. Data Extraction

At the final stage, 62 studies met the inclusion criteria (Figure 1). A study was eligible for data extraction after two independent reviewers reached a consensus on its inclusion in the title, abstract, and full-text review phases. Utilizing the data extraction template in Covidence, we customized a tool to collect general study information, study characteristics, participant characteristics, recording sources and data, feature extraction methods, and machine learning or artificial intelligence model types.

3. Results

3.1. Global Representation

Across 62 studies, 25 countries were represented (Appendix II). The global distribution and frequency of publication are shown in Figure 2. Pediatric populations from the United States, India, and China were the most frequently studied. Data primarily represented pediatric populations from North America, Asia, Europe, and Oceania and less representative of Central and South America, Africa, and the Middle East.

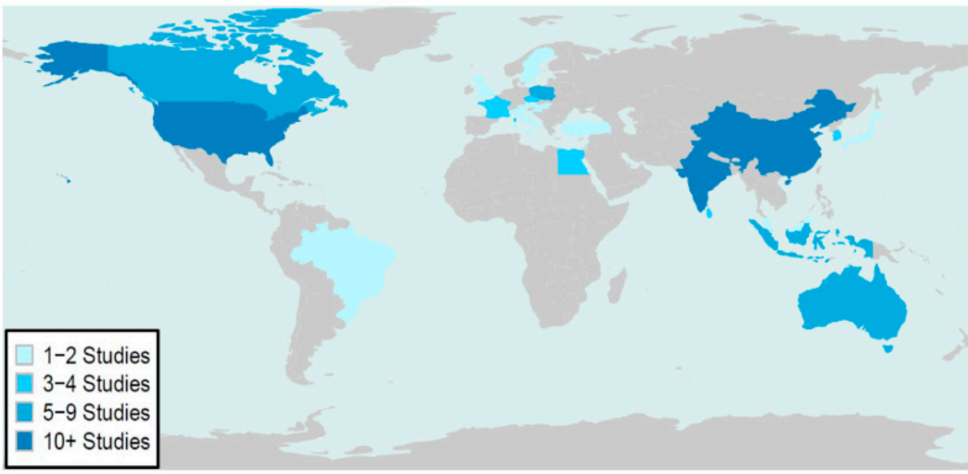

Figure 2. Global heat map of the distribution and frequency of publications included in the scoping review.

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3.2. Studies by Year

This review identified studies published between 2015 and 2023, and data was extracted on May 25, 2023. The number of studies per year is shown in Figure 3, with an average of 7 pediatric voice studies per year between 2015 and 2023 and a peak of 15 publications in 2019.

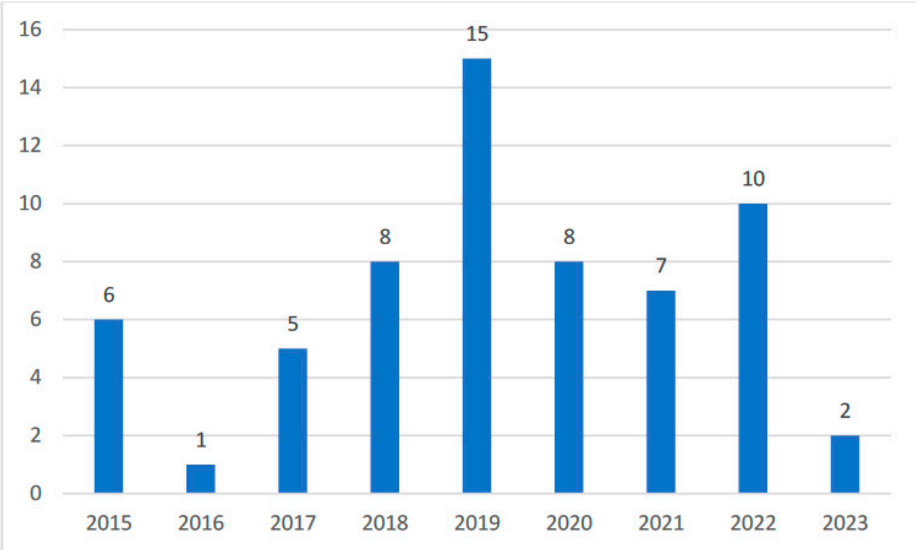

Figure 3. Column graph of publications by year (2015 – 2023) for all studies included in the scoping review.

3.3. Funding Sources

Research funding supported 29 studies (46.7%), and 56 different funding sources were represented (Appendix III). Organizations that provided funding to two or more studies included the National Natural Science Foundation of China, Manipal University Jaipur (India), SMART Innovation Centre (USA), Austrian National Bank, National Institute on Deafness and Other Communication Disorders (USA), Austrian Science Fund, Natural Sciences and Engineering Research Council of Canada, and the Bill & Melinda Gates Foundation (USA). Most funding came from public and private organizations from the United States, China, India, and Austria.

3.4. Participant Age

Each study had, on average, 202 participants [range: 12-2268], with a median of 76 participants. 27% of participants (n = 3347) were distinguished by sex, of which 61% were male. School-aged children (ages 5-12 years) were the most commonly studied (25 studies). Newborn (ages 0-2 months), infant (ages 3-11 months), toddler (ages 1-2 years), preschool (ages 3-4 years), school-aged (ages 5-12 years), and teenage (ages 13-17) groups were also represented in at least 5 studies each as shown in Figure 4. The specific pediatric age group being studied was not defined for 12 studies.

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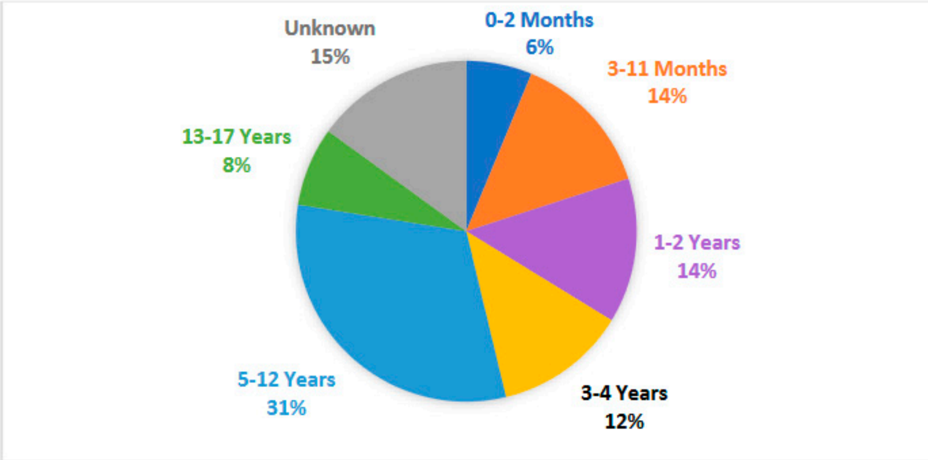

Figure 4. Pie chart of the age distribution of all participants included in the scoping review. Categories: 0-2 months, 3-11 months, 1-2 years, 3-4 years, 5-12 years, 13-17 years, and unknown.

3.5. Recording Characteristics

As shown in Figure 5, studies included three types of vocal recordings: voice (38 studies), cry (13 studies), and respiratory sounds (12 studies). The majority of studies (45 studies) collected unique vocal data, while 17 studies utilized 13 different existing datasets to conduct their studies, of which recordings from the Baby Chillanto Infant Cry Database (Mexico) and the LANNA Research Group Child Speech Database (Czech Republic) were the most commonly studied.

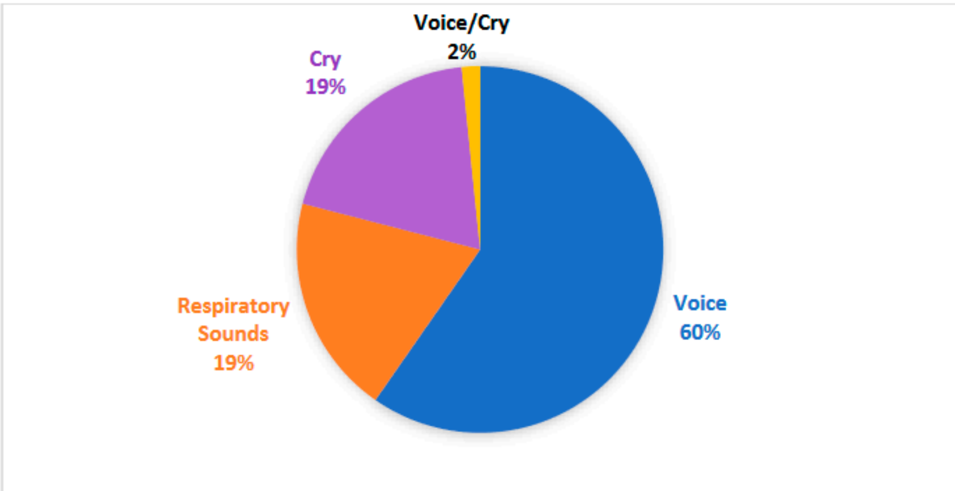

Figure 5. Pie chart of the recording type distribution for all studies included in the scoping review. Categories: Voice, respiratory sounds, cry, and voice & cry.

3.5. Clinical Conditions

Vocal recordings were analyzed using AI as a biomarker for 31 clinical conditions, represented in IV. Among these conditions, developmental conditions (21 studies), respiratory conditions (21 studies), speech and language conditions (13 studies), and non-respiratory conditions (7 studies) were represented. The most frequently studied conditions included Autism Spectrum Disorder (ASD) (12 studies), intellectual disabilities (7 studies), asphyxia (7 studies), and asthma (5 studies).

3.6. Feature Extraction Methods

Among 62 studies, 33 feature extraction methods were utilized (Appendix V). Mel Frequency Cepstral Coefficients were the most utilized feature extraction method (43 studies), followed by

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Spectral Components (10 studies), Cepstral Coefficients (10 studies), Pitch and Fundamental Frequency (9 studies), and Linear Predictive Coefficients (9 studies).

3.7. Artificial Intelligence and Machine Learning Models

Across studies, 33 artificial intelligence or machine learning models were utilized (Appendix VI). The most common AI/ML models were Support Vector Machine (SVM) (34 studies), Neural Network (31 studies), Random Forest (9 studies), Linear Discriminant Analysis (LDA) (7 studies), and K-Nearest Neighbor (KNN) (5 studies).

4. Discussion

The human voice contains unique, complex acoustic markers that vary depending on one's coordination between respiration, phonation, articulation, and prosody. As technology progresses, especially in artificial intelligence and acoustic analysis, voice is emerging as a cost-effective, non-invasive, and accessible biomarker for the detection of pathologies. Our primary objective was to determine what is currently known about using pediatric voice paired with AI models for the early detection, diagnosis, and monitoring of pediatric conditions. This review identified 62 studies that met the inclusion criteria, utilizing pediatric voice, cry, or respiratory sounds for the detection of 31 pediatric conditions among 4 condition groups, representing pediatric populations from 25 countries.

4.1. Developmental Conditions

Twenty-one of the included studies trained and evaluated machine learning algorithms using voice data to classify children with developmental disorders. Speech was the predominantly utilized feature, with studies considering various aspects of speech, including vocal, acoustic, phonetic, and language features. Acoustic features [1–3] and phonetic features [14] were extracted to train machine learning algorithms in classifying children with intellectual disability. A majority of the included studies centered on training machine learning algorithms to classify children with autism spectrum disorder (and Down Syndrome [22]) using acoustic features [16,17,22,29,30,61], vocal features [8,31], voice prosody features [38], prelinguistic vocal features [41], and speech features [15,59]. In particular, Wu et al. (2019) [61] focused on acoustic features of crying sounds in children of 2 to 3 years of age, while Pokorny et al. (2017) [41] concentrated on prelinguistic vocal features in 10-month-old babies. Speech features were also utilized in training machine learning algorithms to classify children with developmental language disorders [63], specific language impairment [50,51], and dyslexia [25,43].

4.2. Respiratory Conditions

Twenty-one of the included studies focused on the unintentional air movement across vocal cords by cry, cough, or breath. Machine learning techniques characterized infant cries in the setting of asphyxia [9,23,24,39,46]. Spontaneous pediatric coughs are rigorously described through AI methodology [5,7,42,47] and analyzed to detect specific clinical entities such as croup [47–49], pertussis [49], asthma [21], and pneumonia [6]. Asthma, a common childhood illness, has also been studied through AI analysis of pediatric breath sounds [12,33].

4.3. Speech and Language Conditions

The detection and evaluation of voice and speech disorders in children is uniquely challenging due to the intricate nature of speech production and the variability inherent in children's speech patterns. To address these challenges, researchers have explored a variety of computational approaches leveraging machine learning, neural networks, and signal processing techniques aimed toward early identification of speech delay [44,52]. Several studies highlight promising methodologies to identify stuttering and specific language impairment (SLI) using acoustic and linguistic features [4,11]. Feature extraction techniques and convolutional neural networks can help to detect hypernasality in children with cleft palates [18,58]. Voice acoustic parameters have been developed to identify dysphonia and vocal nodules in children [54,55]. Automatic acoustic analysis

 doi:10.20944/preprints202405.0889.v1

can also be used to differentiate typically developing children from those who are hard of hearing, language-delayed, and autistic [56]. Other notable research has utilized deep learning models and computer-aided systems to identify SLI and sigmatism, also known as lisping [28,35,60].

4.4. Other Non-Respiratory Conditions

Researchers have explored using voice recordings and AI to identify other non-respiratory genetic or medical conditions, usually based on known characteristics affecting cry, voice, or speech that can lead to a clinical suspicion that a diagnosis is present. A Voice Biometric System was developed using recordings of 15 two-syllable words to identify whether a child has cerebral palsy and the severity of the condition, with potential usefulness to evaluate therapeutic benefit [36]. A hierarchical machine learning model using voice recordings of the standardized PATA speech test was able to identify and grade the level of severity of dysarthria associated with ataxia [54]. Early detection of anxiety and depression using a 3-minute Speech Task in 3 to 8-year-olds showed reasonable accuracy when recordings were high quality [34], and multimodal text and audio data was able to discriminate adolescents with depression based on recorded interviews [62]. Recordings of cry sounds have also been evaluated using machine learning and have shown reasonable accuracy in detecting life-threatening sepsis in neonates [26,27] and neonatal opioid withdrawal syndrome [32].

4.5. Limitations

This review was restricted to studies published in English, which may not capture the full scope of research in non-English-speaking regions. Additionally, the inclusion criteria required a sample size of at least 10 pediatric participants in each study. These studies may offer valuable insights, but they did not meet inclusion criteria within this review.

5. Conclusions

This scoping review highlights the current and potential application of AI in analyzing pediatric voice as a biomarker for health. So far, pediatric voice has been paired with AI models for the early detection, diagnosis, and monitoring of 32 pediatric conditions, primarily observing Autism Spectrum Disorder (ASD), intellectual disabilities, asphyxia, and asthma. While most applications of using pediatric voice as a biomarker have been for the diagnosis of developmental, respiratory, and speech and language conditions, this review highlights the application of pediatric voice analysis for the detection of non-respiratory conditions such as anxiety and depression, sepsis, and jaundice. Research thus far has demonstrated the enormous potential to use voice recordings to detect and monitor diseases and conditions in children. While most research thus far has recorded voice in more clinical settings, one can imagine a future where recordings are used as a biomarker in non-clinical settings where children are more comfortable, such as at home or school. Further development of this field could lead to innovative, new diagnostic tools and interventions for pediatric populations globally.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org. **Appendix I:** A table showing the Boolean search strategy employed to compile studies from PubMed, Cochrane Database, Embase, Web of Science, ClinicalTrials.Gov, and Google Scholar. **Appendix II:** A table listing the country associated with each study and their reference number. **Appendix III:** A table listing the funding source, funding country, study, and reference number for each study that stated a funding source within their respective publication. **Appendix IV:** A table listing the condition group and condition type being analyzed by each study included in the scoping review and their associated reference number. **Appendix V:** A table listing the feature extraction method utilized by each respective study and their associated reference number. **Appendix VI:** A table listing the artificial intelligence or machine learning model utilized by each respective study and their associated reference number. **Appendix VII:** Bridge2AI- Voice Consortium List of Authors.

Author Contributions: Hannah Paige Rogers conducted the comprehensive scoping review, including the design, data collection, analysis, and writing of the manuscript, with contributions from all team members. Stacy

Jo contributed to the data collection and analysis of the scoping review. Dr. Elizabeth Silberholz participated in the development of the search strategy, review of articles, and writing of manuscript. Drs Jung Kim and Anne Hseu participated in the review of articles and writing of manuscript. Anna Dorste conceptualized and executed the search strategies and wrote the methodology portion of the paper concerning the searches and databases. Dr. Kathy Jenkins participated in developing the search strategy and the review of articles, data interpretation, and presentation, and writing of manuscript.

Funding: This research was funded by National Institutes of Health, grant number 1OT20D032720-01.

Institutional Review Board Statement: Not Applicable

Informed Consent Statement: Not Applicable

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: We would like to acknowledge Yaël Bensoussan, MD MSc, Chief of Laryngology at the University of South Florida Morsani College Of Medicine, and Olivier Elemento PhD, Professor of Physiology and Biophysics at Weill Cornell Medicine, for acquiring funding from the National Institutes of Health, allowing this project to be possible. We would also like to acknowledge Jessily Ramirez-Mendoza, EPHM IMPH, for her contribution to the design and implementation of the scoping review.

Conflicts of Interest: The authors declare no conflicts of interest.

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