Health Science Reports

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NARRATIVE REVIEW OPEN ACCESS

Artificial Intelligence in Pediatric Epilepsy Detection: Balancing Effectiveness With Ethical Considerations for Welfare

Marina Ramzy Mourid[1] | Hamza Irfan[2] | Malik Olatunde Oduoye[3]

[1]Faculty of Medicine, Alexandria University, Alexandria, Egypt | [2]Department of Medicine, Shaikh Khalifa Bin Zayed Al Nahyan Medical and Dental College, Lahore, Pakistan | [3]Department of Research, The Medical Research Circle (MedReC), Goma, Democratic Republic of the Congo

Correspondence: Malik Olatunde Oduoye (malikolatunde36@gmail.com)

Received: 9 May 2024 | **Revised:** 22 November 2024 | **Accepted:** 3 January 2025

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | diagnosis | ethical considerations | ethical implications | neurological disorder | patient outcomes | pediatric epilepsy

ABSTRACT

Background and Aim: Epilepsy is a major neurological challenge, especially for pediatric populations. It profoundly impacts both developmental progress and quality of life in affected children. With the advent of artificial intelligence (AI), there's a growing interest in leveraging its capabilities to improve the diagnosis and management of pediatric epilepsy. This review aims to assess the effectiveness of AI in pediatric epilepsy detection while considering the ethical implications surrounding its implementation.

Methodology: A comprehensive systematic review was conducted across multiple databases including PubMed, EMBASE, Google Scholar, Scopus, and Medline. Search terms encompassed "pediatric epilepsy," "artificial intelligence," "machine learning," "ethical considerations," and "data security." Publications from the past decade were scrutinized for methodological rigor, with a focus on studies evaluating AI's efficacy in pediatric epilepsy detection and management.

Results: AI systems have demonstrated strong potential in diagnosing and monitoring pediatric epilepsy, often matching clinical accuracy. For example, AI-driven decision support achieved 93.4% accuracy in diagnosis, closely aligning with expert assessments. Specific methods, like EEG-based AI for detecting interictal discharges, showed high specificity (93.33%–96.67%) and sensitivity (76.67%–93.33%), while neuroimaging approaches using rs-fMRI and DTI reached up to 97.5% accuracy in identifying microstructural abnormalities. Deep learning models, such as CNN-LSTM, have also enhanced seizure detection from video by capturing subtle movement and expression cues. Non-EEG sensor-based methods effectively identified nocturnal seizures, offering promising support for pediatric care. However, ethical considerations around privacy, data security, and model bias remain crucial for responsible AI integration.

Conclusion: While AI holds immense potential to enhance pediatric epilepsy management, ethical considerations surrounding transparency, fairness, and data security must be rigorously addressed. Collaborative efforts among stakeholders are imperative to navigate these ethical challenges effectively, ensuring responsible AI integration and optimizing patient outcomes in pediatric epilepsy care.

Summary

- Epilepsy is hazardous in children due to its potential to slow developmental progress and impair skill acquisition.
- Artificial intelligence has shown promising success in diagnosing epilepsy in children, often rivaling traditional methods.
- Accurate algorithms can facilitate early and precise diagnoses of epilepsy in children.

1 | Introduction

Epilepsy is the second most common neurological disorder, following Alzheimer's disease [1]. This brain disorder causes recurrent seizures and is particularly hazardous in children due to its potential to slow developmental progress and impair skill acquisition. The link between epilepsy and personality changes was first recognized by American and Canadian neurologists in the 1950s, marking the beginning of modern epilepsy research [2]. Phenytoin, the first antiepileptic drug introduced during this era, remains in use today [2]. Early detection and understanding of epilepsy's severity are crucial, with numerous studies, especially those employing machine learning (ML) techniques, showing promise in improving early diagnosis [3]. Globally, epilepsy affects around 50 million people, or 1% of the population, with approximately 0.654% of the population in Saudi Arabia suffering from the condition [4]. The manifestation of epilepsy varies with age; newborns might experience symptoms due to oxygen deprivation at birth or abnormal brain development, whereas infants could show signs related to brain tumors or genetic conditions [5]. Accurate diagnosis is therefore vital. The use of ML in detecting epilepsy in children brings up several ethical issues, such as data protection, algorithm transparency, and accountability. These factors are fundamental to maintaining the trust of both patients and healthcare providers. The ethical challenges extend to research design and the selection of algorithms to prevent harmful outcomes that contravene ethical medical practice standards. Since children, particularly those under 18, cannot consent independently, it is crucial to establish a clear communication protocol with parents or guardians. This protocol should explain how ML tools will be used and how their children's data will be managed. Additionally, the potential for biases in algorithms, which might be trained predominantly on adult data, needs careful consideration [6]. Such biases could lead to inaccurate diagnoses or inappropriate treatment recommendations for children, highlighting the necessity of utilizing pediatric datasets in model training and validation [7]. Moreover, while ML can enhance clinical decision-making, it should complement rather than replace the expertize of medical professionals. This review discusses the necessary balance between the effectiveness of machine learning applications in pediatric epilepsy detection and the ethical considerations that safeguard child welfare.

2 | Methodology

The literature for this review was obtained through an electronic search of databases including PubMed, EMBASE, Google Scholar, Scopus, and Medline, using search terms such as "artificial intelligence," "ethical considerations," "effectiveness," "epilepsy," "children," "pediatric epilepsy," "machine learning," "deep learning," "neural networks," "ethics," "morality," "privacy," "data security," "patient rights," "healthcare technology," and "medical ethics." The search was limited to publications within the past 10 years. Manual searches were also conducted. Full-text publications were assessed for potential inclusion. Publications lacking detailed methods or containing redundant content were excluded from the review.

3 | Findings

3.1 | Effectiveness of AI in Pediatric Epilepsy Detection in Children

Artificial Intelligence (AI) has shown promising success in diagnosing epilepsy in children, often rivalling traditional methods. For instance, an AI-driven decision support system for diagnosing epilepsies in children matched the diagnoses of an experienced doctor in 85.2% of cases, and closely matched in another 8.2%, achieving an overall success rate of 93.4% [8]. Another study utilized a hybrid approach where human raters used operational criteria for interictal epileptiform discharge (IED) on AI-detected events, achieving high specificity (93.33%–96.67%) and good sensitivity (93.33%–76.67%), with the accuracy comparable to conventional EEG readings while significantly reducing the time burden [9]. AI's efficacy, however, varies across different types or forms of epilepsy. In temporal lobe epilepsy (TLE), AI classification models using MRI data have demonstrated moderate accuracy in identifying patients with hippocampal sclerosis, achieving accuracies between 68% and 76%. However, these models show reduced accuracy, ranging from 53% to 62%, when classifying patients without detectable lesions [10]. AI has also successfully classified epilepsy types using ontology-based and genetics-based machine learning methods and has predicted therapeutic responses to valproic acid in childhood absence epilepsy through EEG analysis. Future AI developments may focus on refining models to accurately identify specific electrographic biomarkers of epilepsy, such as spikes, high-frequency oscillations, and seizure patterns. Integrating AI to analyse EEG alongside clinical and behavioral data could optimize epilepsy therapy [11]. Advances might also include developing multimodal AI systems that combine EEG and ECG data for improved seizure identification across different settings [12].

Additionally, deep learning (DL) could become crucial in neuroimaging, particularly in the presurgical evaluation of drug-refractory epilepsy, aiding in the detection of subtle abnormalities that are not obvious through visual inspection. The outcomes of machine learning diagnoses and their communication with children and their families can greatly influence their confidence in future medical interventions. According to a study by Wong et al. medical professionals involved in epilepsy management are receptive to adopting ML seizure detection tools and are willing to undergo training [13]. This indicates that when effectively communicated by well-informed healthcare professionals, families and children may develop a positive outlook towards these interventions. Furthermore, Monfort et al. underscored the importance of considering patient and caregiver acceptability when designing technological devices for seizure detection, noting varying levels of support that could affect the confidence placed in these technologies and their outcomes [14].

DL systems for seizure video analysis have shown substantial promise in enhancing the detection, classification, and analysis of seizures, particularly in challenging cases such as pediatric epilepsy, where signs are often more subtle. Aristizabal et al. comprehensively evaluated the range of deep learning systems in detecting, classifying, and analyzing seizure events [15]. Key technologies include convolutional neural networks (CNNs) and recurrent neural networks (RNNs), as well as hybrid architectures like CNN-LSTM models that combine both spatial and temporal data to improve the accuracy of seizure detection and progression analysis [16, 17]. Notably, human pose estimation (HPE) methods, both 2D and 3D, have also proven effective in tracking body positions and joint movements, which are critical for distinguishing between seizure-related activity and normal movement [18]. Additionally, advanced techniques such as Optical Flow can capture minute motion details that signal the onset of seizures [19]. Models focused on face and hand detection, including Faster R-CNN, Mask R-CNN, and SSD, have also been employed to detect subtle facial expressions and hand movements that can provide early indications of seizure activity [20]. Furthermore, multi-layered frameworks like the Nelli hybrid system integrate various AI techniques, including 2D and 3D pose estimation, optical flow, and support vector machines (SVMs), to offer enhanced diagnostic accuracy and classification of seizure types. These hybrid systems excel by combining different models to improve detection performance [21].

While Optical Flow identifies minute changes in movement, pose estimation helps track body posture, and SVMs contribute to distinguishing between different seizure types. Despite the significant potential of these AI-driven tools, the implementation of such systems introduces important ethical and privacy concerns. Seizure detection systems often rely on sensitive personal data, such as video footage or biometric information, which raises privacy risks, especially when applied to vulnerable populations like children [22]. Ensuring robust data security, and privacy protection, and obtaining informed consent for data use are essential to address these concerns. Additionally, the potential for model bias, which could lead to inaccuracies across diverse patient groups, must be considered to ensure the generalizability and fairness of these AI systems in clinical settings. Thus, while these advancements hold promise, balancing technological innovation with ethical considerations remains crucial for the successful adoption of AI in healthcare [15].

Karácsony et al. explored deep learning models for pediatric epilepsy detection through in-bed movement monitoring in clinical settings. The study examined RGB-based and skeleton-based models, each with specific advantages. RGB-based models, using CNNs, RNNs, and Transformers, capture detailed appearance information but are sensitive to noise, occlusions, and lighting changes, limiting real-time applicability in clinical environments. In contrast, skeleton-based models focus on essential body key points (e.g., joint positions), making them more robust against occlusions and background interference. Graph convolutional networks (GCNs) such as MS-G3D and ST-GCN++ analyze body movements as connected points, allowing spatiotemporal analysis that generalizes well across patients. The study suggests a two-stage model: first, capturing movement patterns via skeleton/3D pose models, using transfer learning from general datasets; second, classifying seizure-specific activity. This setup enhances system efficiency and explainability, enabling clinicians to interpret quantified movement features, and making it suitable for diagnostic support with minimal seizure-specific data [23]. Looking forward, advancing pediatric epilepsy detection will require robust models that can manage partial occlusions from blankets and medical personnel and cope with the low-resolution video quality commonly found in overnight monitoring. Synthetic data augmentation, especially occlusion-aware training, is expected to play a significant role in overcoming these challenges by simulating realistic clinical scenarios, making it feasible to generate extensive datasets for training.

3.2 | Ethical Considerations of AI for the Management of Epilepsy in Children

Ethical considerations surrounding the implementation of AI in pediatric epilepsy management encompass a variety of domains, including autonomy, fairness, bias mitigation, data security, and transparency. Concerns related to autonomy stem from the inherent complexity and opacity of AI systems, which could diminish transparency and reduce clinician oversight, thereby potentially diminishing patient involvement in decision-making processes [24]. To ensure fairness, it is critical to undertake rigorous evaluations and adjustments of AI algorithms to effectively mitigate biases that may disproportionately influence treatment outcomes across diverse patient demographics [24]. In ensuring the ethical deployment of AI in pediatric epilepsy diagnosis and management, it is crucial to prioritize areas such as data security and privacy, algorithmic transparency, data standardization, and interoperability across different platforms. These measures are essential to maintain patient confidentiality and uphold data integrity throughout the lifecycle of AI applications, thereby guiding the ethical design, implementation, and usage of AI systems. Moreover, the establishment of transparent decision-making processes in the use of AI for pediatric epilepsy is vital to cultivate trust and comprehension among all stakeholders involved.

Healthcare professionals should focus on enhancing transparency in the mechanisms of AI algorithms and their decision-making processes to promote collaboration and augment patient outcomes [25]. Adherence to established guidelines for conducting ethical AI research in neurology is imperative to navigate the complexities associated with AI implementations, while ensuring that ethical standards are maintained and transparency in decision-making is achieved [25]. Collaboration with healthcare professionals is paramount for the successful integration of AI into pediatric epilepsy care. By fostering collaborative opportunities, promoting research excellence, and spearheading educational initiatives, the understanding and acceptance of AI technologies among healthcare professionals can be significantly enhanced, thereby facilitating their effective utilization in clinical practice [26]. Engaging healthcare professionals in the development and implementation of AI tools is crucial to align these innovations with clinical needs, ethical standards, and professional workflows, promoting a collaborative and patient-centered approach to care. This type of collaboration not only fosters the adoption of AI but also encourages interdisciplinary teamwork and knowledge exchange, which are instrumental in improving patient outcomes and maintaining ethical practices.

3.3 | Striking a Balance

Pediatric epilepsy is a complex neurological condition characterized by recurrent seizures, impacting cognitive development, emotional well-being, and overall quality of life in affected children [27]. Timely detection and intervention are paramount for improving outcomes in pediatric epilepsy [28]. The integration of AI and ML technologies in epilepsy diagnosis and management has emerged as a promising avenue to enhance diagnostic accuracy and optimize treatment strategies. However, this technological advancement necessitates careful consideration of ethical implications to ensure patient safety and well-being [29]. AI applications in pediatric epilepsy leverage diverse datasets, including electroencephalogram (EEG) recordings, magnetic resonance imaging (MRI) scans, and electronic health records (EHRs), to classify seizure types, identify focal lesions, predict treatment responses, and optimize patient care pathways [30].

For instance, researchers have successfully utilized AI algorithms to detect and characterize focal lesions in medication-resistant epilepsy cases, guiding treatment decisions, including the consideration of surgical interventions based on lesion localization. Shuang et al. utilized AI-driven deep-learning models to detect epileptic seizures using wrist- or ankle-worn wearable devices. They collected electrodermal activity, accelerometry (ACC), and photoplethysmography data from patients in an epilepsy monitoring unit. The AI models applied to this data achieved a sensitivity of 83.9% and a false positive rate of 35.3% with ACC and BVP data fusion [31]. This study underscores the potential of AI-enabled noninvasive seizure detection using wearables and personalized approaches in epilepsy care.

Focal cortical dysplasia (FCD) is a frequent cause of drug-resistant focal epilepsy [32]. Nevertheless, FCDs are frequently not visible on standard MRI scans, and the pre-surgical diagnosis relies significantly on the examiner's expertize. Hannah et al. used AI to develop a neural network for detecting focal cortical dysplasia (FCD) using MRI data. They trained the model on a cohort of 1015 participants with FCD-related epilepsy and controls from 22 centers worldwide. The AI algorithm achieved a sensitivity of 67% and specificity of 54% on a test cohort, with higher sensitivity (85%) in seizure-free patients with FCD type IIB [33]. Individual reports from the AI system highlighted lesion locations and imaging features, showcasing AI's potential for FCD detection in epilepsy patients. The perspectives of youths on the ethical use of AI in healthcare underscore the importance of patient engagement and shared decision-making. A study by Kelly et al. showed that children and adolescents exhibit a positive attitude towards AI applications intended to benefit others, emphasizing the significance of respecting patient preferences and maintaining the patient-physician relationship [34].

Avani et al. conducted a randomized controlled trial involving 30 children with new-onset epilepsy and their caregivers. They aimed to assess a family-tailored adherence intervention (AI) to improve adherence to antiepileptic drugs. Participants used electronic monitors to track adherence for 1 month. Those with less than 90% adherence were randomized into either the AI group (receiving four intervention sessions over 2 months) or a treatment-as-usual group. Preliminary findings demonstrated that the AI intervention was feasible and acceptable, with the AI group showing enhanced adherence [35].

The application of AI in non-EEG-based modalities for pediatric epilepsy detection has also gained significant attention in recent years. Various machine learning techniques have been employed to analyze neuroimaging data, including resting-state functional MRI (rs-fMRI), diffusion tensor imaging (DTI), and wearable or sensor-based technologies such as accelerometry, heart rate, and electrodermal activity. These AI-driven approaches aim to improve seizure detection, enhance diagnostic accuracy, and provide real-time monitoring, particularly in cases of nocturnal seizures or in children who may not exhibit obvious seizure activity during routine clinical assessments. For example, rs-fMRI has been utilized to identify functional connectivity patterns associated with seizure onset zones (SOZ) and epileptogenic zones (EZ) in patients with temporal lobe epilepsy (TLE). Machine learning algorithms applied to rs-fMRI data can achieve classification accuracies up to 97.5% [36], though the variability in hemodynamic responses and the complexity of interpreting the data remain challenges. Similarly, DTI, which assesses the integrity of white matter tracts in the brain, has been combined with machine learning models to detect microstructural changes indicative of epilepsy. Studies have shown that DTI-derived metrics, such as fractional anisotropy (FA) and mean diffusivity (MD), can help differentiate between healthy controls and children with epilepsy, although interpreting diffusion metrics is complex and sensitive to motion artefacts [37].

In addition to neuroimaging, sensor-based modalities like accelerometry and heart rate monitoring have been explored for nocturnal seizure detection. A study combined accelerometry and heart rate data using the Night Watch system to detect nocturnal motor seizures in children, achieving excellent sensitivity [38]. Similarly, a heart rate and positional adjustment algorithm based on accelerometry was employed to detect nocturnal seizures, yielding high sensitivity both before and after adjustments [39]. Additionally, audio-video monitoring systems were used to automatically detect and classify various types of nocturnal seizures with notable accuracy. These systems, however, may be less sensitive to seizures involving low motion or subtle manifestations [21, 40]. These AI-based non-EEG approaches highlight the potential of combining neuroimaging and sensor technologies to enhance the detection and monitoring of epilepsy, particularly in challenging scenarios such as nocturnal seizures or in pediatric populations. However, challenges remain regarding the integration of multimodal data, the need for large, diverse datasets to train robust models, and the variability in individual responses to seizures, which can impact the sensitivity and reliability of these systems.

A detailed overview of both EEG-based [29, 41–49] and non-EEG based studies [21, 36–40, 50–54] and their corresponding accuracy is presented in Table 1: A detailed overview of both EEG based and Non-EEG based studies and their corresponding accuracy in detecting Epilepsy and seizures.

TABLE 1 | A detailed overview of both EEG-based and non-EEG based studies and their corresponding accuracy in detecting Epilepsy and seizures.

EEG-based studies			
Study	**Type of data**	**Algorithms**	**Accuracy**
Tiwari et al. 2016 [41]	EEG record	Utilized **Local Binary Pattern (LBP)** and **Support Vector Machine (SVM)** for seizure detection based on EEG data.	98.80%
Kabir and Siuly, 2016 [42]	EEG record	Combined **Logistic Model Trees (LMT)**, **Multinomial Logistic Regression (MLR)**, and **Support Vector Machine (SVM)** for classification of EEG data.	LMT: 95.33%
Tharayil et al. 2017 [43]	EEG record (adults and children)	Applied **Linear Mixed Model** to EEG data from adults and children for seizure analysis.	Adults: 82%, Children: 76%
Usman and Usman, 2017 [44]	EEG record	Used **Support Vector Machine (SVM)** for seizure detection based on EEG signals.	92.23%
Jaiswal and Banka, 2018 [45]	EEG record	Combined **Sub-pattern and Cross-sub-pattern Correlation-based PCA (SpPCA and SubXPCA)** with **Support Vector Machine (SVM)** for EEG signal classification.	100%
Subasi, 2019 [46]	EEG record	Employed **Genetic Algorithm (GA)** and **Particle Swarm Optimization (PSO)** in conjunction with **Support Vector Machine (SVM)** for seizure detection.	99.38%
Ilakiyaselvan et al. 2020 [47]	Recurrence plot of EEG record	Applied **Deep Learning (DL)** algorithms to recurrence plots of EEG data for binary and tertiary classification.	Binary: 98.5%, Tertiary: 95%
Brari and Belghith, 2021 [48]	EEG record	Implemented **Machine Learning with Correlation Dimension (CD)** for seizure detection from EEG signals.	100%
Nair et al. 2021 [29]	EEG record	Employed **k-Nearest Neighbors (kNN)** and a variety of **AI and ML algorithms** for EEG data analysis.	—
Natu et al. 2022 [49]	EEG record	Applied a combination of **Artificial Intelligence (AI)**, **Machine Learning (ML)**, and **Deep Learning (DL)** algorithms for EEG signal analysis.	—
Non-EEG-based studies			
Study	**Type of data**	**Algorithms**	**Accuracy**
van Westrhenen et al. 2023 [38]	Multimodal (accelerometry and heart rate)	Used a **multimodal approach combining accelerometry and heart rate** for nocturnal motor seizure detection in children using NightWatch system.	Sensitivity: 100% (median per participant)
Armand Larsen et al. 2022 [40]	Audio-video system	Applied **automated audio-video analysis** for detecting nocturnal motor seizures, distinguishing between Tonic-Clonic Seizures (TCS), Hyperkinetic Motor Seizures (HMS), and Myoclonic Motor Seizures (MMS).	Sensitivity: 100% for TCS, 80% for HMS, 8.3% for MMS
Lazeron et al. 2022 [39]	Accelerometry and heart rate	Used a **heart rate and positional adjustment algorithm** for detecting nocturnal motor seizures based on accelerometry and heart rate.	Sensitivity: 79.9% before adjustment, 79.4% after adjustment

(Continues)

TABLE 1 | (Continued)

Non-EEG-based studies			
Study	**Type of data**	**Algorithms**	**Accuracy**
Onorati et al. 2021 [50]	Multimodal (accelerometry and electrodermal activity)	Combined **accelerometry and electrodermal activity** to detect tonic-clonic seizures in both children and adults.	Sensitivity: 92% (children), 94% (adults)
Japaridze et al. 2022 [51]	Wearable EEG-headband	Developed a specialized **EEG-based algorithm** for detecting absence seizures using a wearable EEG-headband.	Sensitivity: Average 78.8%, Median 92.9%
Basnyat et al. 2022 (Nelli) [21]	Audio-video system	Semi-automated hybrid video/audio monitoring system used in a home setting for detecting epileptic and nonepileptic events.	Clinical Utility: 80% recognition of clinically relevant events; 65% for epileptic seizures
Li Kang et al. 2021 [37]	Diffusion Kurtosis Imaging (DKI)	Used Diffusion Kurtosis Imaging (DKI) to analyze hippocampal data, followed by a Support Vector Machine (SVM) for classification of epilepsy versus controls.	95.24% (patient vs. normal controls)
Rose Dawn Bharath, 2019 [36]	Resting-state fMRI (rsfMRI)	Applied **Probabilistic Independent Component Analysis (PICA)**, **Elastic Net for feature selection**, and **Support Vector Machine (SVM)** to classify epilepsy networks in TLE patients using rsfMRI data.	97.5% (Sensitivity: 100%, specificity: 94.4%)
Beniczky et al. 2018 [52]	Surface electromyography (EMG)	Employed a **real-time EMG-based detection algorithm** for identifying tonic-clonic seizures.	Sensitivity: 94%
Arends et al. 2018 [53]	Accelerometry and heart Rate	Used a **multimodal algorithm combining heart rate and motion data** to detect tonic-clonic seizures.	Sensitivity: 81%
Beniczky et al. 2013 [54]	Accelerometry	Applied **accelerometry-based detection** for identifying tonic-clonic seizures.	Sensitivity: 90%

3.4 | Challenges and Recommendations

The effectiveness of machine learning in diagnosing epilepsy can have profound effects on a child's psychological health and social dynamics. Accurate algorithms can facilitate early and precise diagnoses, potentially improving the management of epilepsy and reducing the psychological stress associated with the unpredictability of seizures [55]. This improved management can boost a child's self-esteem and social life by enhancing seizure control and mitigating the stigma and social challenges linked to visible seizure episodes. In contrast, inaccuracies in machine learning algorithms can lead to misdiagnosis or delayed diagnosis, adversely impacting the child's psychological well-being [56, 57]. False positives may provoke unnecessary anxiety and social isolation, fearing non-existent seizures, while false negatives might result in inadequate medical interventions, exposing the child to preventable seizure-related injuries or psychosocial difficulties due to uncontrolled epilepsy [30]. Additionally, self-esteem is known to mediate the relationship between epilepsy-related and environmental factors and mental health outcomes in youths with epilepsy, suggesting that supporting self-esteem might buffer against the negative mental health impacts of resistant epilepsy or poor peer support [58]. The reliability of machine learning tools also significantly affects a child's trust in medical professionals and the healthcare system overall. When these tools provide accurate, reliable diagnoses, they can strengthen trust by ensuring timely and precise identification of epilepsy, leading to effective treatment strategies. While AI systems show significant promise in the detection and management of pediatric epilepsy, a more balanced view is necessary to fully understand both the potential benefits and risks associated with their use. While the advantages of AI, including enhanced diagnostic accuracy and the ability to process complex data efficiently, are evident, it is equally important to assess the limitations and risks these systems pose critically.

One primary concern is the over-reliance on AI systems in clinical practice. While AI can assist in the analysis of vast amounts of data, there is a risk that clinicians may defer too heavily to AI models, potentially diminishing clinical judgment. This could result in an overdependence on automated outputs without sufficient oversight from healthcare professionals, leading to misdiagnoses or delayed diagnoses [59].

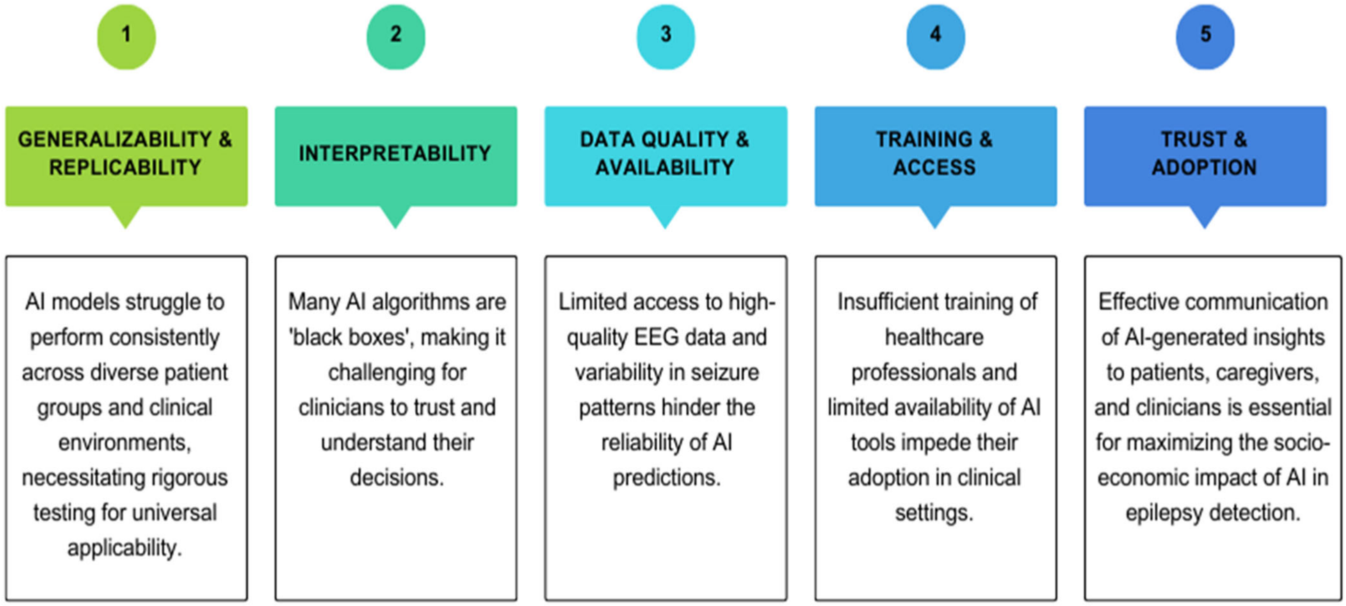

FIGURE 1 | Key challenges in integrating AI for epilepsy detection.

In addition to the risks of over-reliance on AI systems, there are concerns about the quality and methodological rigor of the studies reviewed. Although many report positive results, the variability in study design, sample sizes, and clinical protocols raises questions about the robustness and generalizability of their findings. AI performance also varies across different epilepsy types, highlighting a key area for further research. This variability affects the accuracy of AI models, particularly for epilepsy types without clear biomarkers. Additionally, factors like seizure frequency, manifestation, and individual patient characteristics can significantly impact the effectiveness of AI-driven diagnostic tools. Finally, the challenges of translating AI models from controlled research settings to real-world clinical practice must not be overlooked. While studies demonstrate promising results in AI-driven pediatric epilepsy detection, the practical application of these systems in diverse clinical environments introduces numerous hurdles. Variations in patient demographics, data quality, and clinical expertize can all impact the performance of AI models [60]. Additionally, the integration of AI into existing healthcare systems requires addressing issues such as data standardization, interoperability, and the potential for biases across different patient groups. AI systems need to be adaptable to these diverse conditions in order to be reliable and effective in real-world clinical settings. The figure below presents key challenges in AI integration for epilepsy detection. Figure 1: Key Challenges in Integrating AI for Epilepsy Detection.

4 | Conclusion

The application of AI and ML technologies in pediatric epilepsy can be transformational in terms of improving the diagnostic approach, therapeutic strategies, and psychosocial challenges of young patients with epilepsy. AI can help improve the diagnostic approach by enhancing seizure categorization, aiding prognostication and contributing to further analysis of long-term outcomes. Additionally, AI and ML technologies can optimize therapeutic strategies by making test development more efficient, streamlining treatment by assisting neurologists, as well as enhancing patient adherence therapeutically. Additionally, AI interfaces can be developed to optimize the identification and prevention of treatment-related adverse events for young patients with this complex condition. These strategies can improve the overall health of young epilepsy patients and their caregivers. The ethical considerations regarding the introduction of AI in pediatric epilepsy are manifold but can be distilled into several key themes. These include transparency, fairness, bias minimization, data security, data protection and patient autonomy. It is important to evaluate and adjust AI to balance the underlying data and address any potential biases that might lead to inequitable treatment outcomes between demographic groups. Given the importance of patient confidentiality, data security, algorithmic transparency and adherence to ethical guidelines remain paramount.

By involving both patients and caregivers in AI development, stakeholders can ensure that these healthcare interventions are accepted and inspire confidence. By learning about patients' experiences with technology, we can adjust how we communicate and guide decision-making to fit their expectations and concerns. Patients should be incorporated into these ongoing efforts to ensure that AI is seamlessly incorporated into pediatric epilepsy care. A forward-looking approach can emphasize exceptional clinical outcomes while adhering to ethical principles and keeping the needs and desires of the patient at the forefront of the healthcare experience. Going forward, investigations should focus on refining AI models to accurately detect distinct electrographic markers of epilepsy, incorporating AI with clinical and behavioral data to optimize therapy, and developing multimodal AI systems to improve seizure detection. AI technologies show promise in revolutionizing the care of pediatric epilepsy and, with careful consideration of ethical questions and collaborative partnerships, can improve patient outcomes, enable overall well-being and maintain integrity in the eyes of patients.

Author Contributions

All authors contributed equally to this work.

Acknowledgments

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

Transparency Statement

The lead author Marina Ramzy Mourid affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

References

1. F. L. Scatolini, K. P. Zanni, and L. I. Pfeifer, "The Influence of Epilepsy on Children's Perception of Self-Concept," *journal-title* 69 (2017): 75–79, https://pubmed.ncbi.nlm.nih.gov/28236726/.

2. M. Morningstar, R. C. French, W. I. Mattson, D. J. Englot, and E. E. Nelson, "Social Brain Networks: Resting-State and Task-Based Connectivity in Youth With and Without Epilepsy," *Neuropsychologia [Internet]* 157, no. 107882 (2021): 107882, https://pubmed.ncbi.nlm.nih.gov/33964273/.

3. K. M. Alalayah, E. M. Senan, H. F. Atlam, I. A. Ahmed, and H. S. A. Shatnawi, "Effective Early Detection of Epileptic Seizures Through EEG Signals Using Classification Algorithms Based on T-Distributed Stochastic Neighbour Embedding and K-Means," *Diagnostics (Basel) [Internet]* 13, no. 11 (2023): 1957, https://doi.org/10.3390/diagnostics13111957.

4. S. A. Khan, "Epilepsy Awareness in Saudi Arabia," *Neurosciences* 20, no. 3 (2015): 205–206, https://doi.org/10.17712/nsj.2015.3.20150338.

5. C. P. Panayiotopoulos, *Neonatal Seizures and Neonatal Syndromes* (London, England: Bladon Medical Publishing, 2005).

6. L. H. Nazer, R. Zatarah, S. Waldrip, et al., "Bias in Artificial Intelligence Algorithms and Recommendations for Mitigation," *PLOS Digital Health* 2, no. 6 (2023): e0000278, https://doi.org/10.1371/journal.pdig.0000278.

7. B. D. Wissel, H. M. Greiner, T. A. Glauser, et al., "Investigation of Bias in an Epilepsy Machine Learning Algorithm Trained on Physician Notes," *Epilepsia [Internet]* 60, no. 9 (2019): e93–e98, https://doi.org/10.1111/epi.16320.

8. K. M. Vassilakis, L. Vorgia, and S. Micheloyannis, "Decision Support System for Classification of Epilepsies in Childhood," *Journal of Child Neurology* 17, no. 5 (2002): 357–362, https://doi.org/10.1177/088307380201700509.

9. M. A. Kural, J. Jing, F. Fürbass, et al., "Accurate Identification of EEG Recordings With Interictal Epileptiform Discharges Using a Hybrid Approach: Artificial Intelligence Supervised by Human Experts," *Epilepsia* 63, no. 5 (2022): 1064–1073, https://doi.org/10.1111/epi.17206.

10. E. Gleichgerrcht, B. C. Munsell, S. Alhusaini, et al., "Artificial Intelligence for Classification of Temporal Lobe Epilepsy With ROI-Level MRI Data: A Worldwide ENIGMA-Epilepsy Study," *NeuroImage Clinical* 31, no. 102765 (2021): 102765, https://doi.org/10.1016/j.nicl.2021.102765.

11. A. Knight, T. Gschwind, P. Galer, et al., "Artificial Intelligence in Epilepsy Phenotyping," *Epilepsia*. Published ahead of print, November 20, 2023, https://doi.org/10.1111/epi.17833.

12. Y. Yang, N. D. Truong, J. K. Eshraghian, C. Maher, A. Nikpour, and O. Kavehei, "A Multimodal AI System for Out-of-Distribution Generalization of Seizure Identification," *IEEE Journal of Biomedical and Health Informatics* 26, no. 7 (2022): 3529–3538, https://doi.org/10.1109/JBHI.2022.3157877.

13. S. Wong, A. Simmons, J. Rivera-Villicana, et al., "EEG-Based Automated Seizure Detection - A Survey of Medical Professionals," *Epilepsy & Behavior: E&B* 149, no. 109518 (2023): 109518, https://doi.org/10.1016/j.yebeh.2023.109518.

14. E. Monfort, C. Poulet, C. Nahas, S. Bakridan, L. Clair, and P. Latour, "Clustering Patients and Caregivers for Technology Design: A Step Prior to the Design of an Innovative Technological Device for the Detection of Epileptic Seizures," *Epilepsy & Behavior: E&B* 122, no. 108233 (2021): 108233, https://doi.org/10.1016/j.yebeh.2021.108233.

15. A.-A. David, M. A. Armin, H. Zeeshan, et al., "Deep Learning Approaches for Seizure Video Analysis: A Review," *arXiv* (2023): 109735, http://arxiv.org/abs/2312.10930.

16. T. K. Murugan and A. Kameswaran, "Employing Convolutional Neural Networks and Explainable Artificial Intelligence for the Detection of Seizures From Electroencephalogram Signal," *Results in Engineering* 24 (2024): 103378, https://linkinghub.elsevier.com/retrieve/pii/S2590123024016311.

17. G. Xu, T. Ren, Y. Chen, and W. Che, "A One-Dimensional CNN-LSTM Model for Epileptic Seizure Recognition Using EEG Signal Analysis," *Frontiers in Neuroscience* 14 (2020): 578126, https://doi.org/10.3389/fnins.2020.578126.

18. G. Lan, Y. Wu, F. Hu, and Q. Hao, "Vision-Based Human Pose Estimation via Deep Learning: A Survey," *arXiv* (2023): 1–16, http://arxiv.org/abs/2308.13872.

19. J. R. Martin, P. G. Gabriel, J. J. Gold, et al., "Optical Flow Estimation Improves Automated Seizure Detection in Neonatal EEG," *Journal of Clinical Neurophysiology* 39, no. 3 (2022): 235–239, https://doi.org/10.1097/WNP.0000000000000767.

20. D. Ahmedt-Aristizabal, M. A. Armin, Z. Hayder, et al., "Deep Learning Approaches for Seizure Video Analysis: A Review," *Epilepsy & Behavior: E&B* 154, no. 109735 (2024): 109735, https://doi.org/10.1016/j.yebeh.2024.109735.

21. P. Basnyat, J. Mäkinen, J. T. Saarinen, and J. Peltola, "Clinical Utility of a Video/Audio-Based Epilepsy Monitoring System Nelli," *Epilepsy & Behavior: E&B* 133, no. 108804 (2022): 108804, https://doi.org/10.1016/j.yebeh.2022.108804.

22. C. Maher, Y. Yang, N. D. Truong, C. Wang, A. Nikpour, and O. Kavehei, "Seizure Detection With Reduced Electroencephalogram Channels: Research Trends and Outlook," *Royal Society Open Science* 10, no. 5 (2023): 230022, https://doi.org/10.1098/rsos.230022.

23. T. Karácsony, L. A. Jeni, F. De la Torre, and J. P. S. Cunha, "Deep Learning Methods for Single Camera-Based Clinical In-Bed Movement Action Recognition," *Image and Vision Computing* 143, no. 104928 (2024): 104928, https://doi.org/10.1016/j.imavis.2024.104928.

24. D. Ueda, T. Kakinuma, S. Fujita, et al., "Fairness of Artificial Intelligence in Healthcare: Review and Recommendations," *Japanese Journal of Radiology* 42, no. 1 (2024): 3–15, https://doi.org/10.1007/s11604-023-01474-3.

25. A. Kiseleva, D. Kotzinos, and P. De Hert, "Transparency of AI in Healthcare as a Multilayered System of Accountabilities: Between Legal Requirements and Technical Limitations," *Frontiers in Artificial Intelligence* 5 (2022): 879603, https://doi.org/10.3389/frai.2022.879603.

26. S. A. Alowais, S. S. Alghamdi, N. Alsuhebany, et al., "Revolutionizing Healthcare: The Role of Artificial Intelligence in Clinical

Practice," *BMC Medical Education* 23, no. 1 (2023): 689, https://doi.org/10.1186/s12909-023-04698-z.

27. A. Rozensztrauch and A. Kołtuniuk, "The Quality of Life of Children With Epilepsy and the Impact of the Disease on the Family Functioning," *International Journal of Environmental Research and Public Health* 19, no. 4 (2022): 2277, https://doi.org/10.3390/ijerph19042277.

28. M. Waak, K. Gibbons, L. Sparkes, et al., "Real-Time Seizure Detection in Paediatric Intensive Care Patients: The RESET Child Brain Protocol," *BMJ Open* 12, no. 6 (2022): e059301, https://doi.org/10.1136/bmjopen-2021-059301.

29. P. P. Nair, R. Aghoram, and M. L. Khilari, "Applications of Artificial Intelligence in Epilepsy," *International Journal of Advanced Medical and Health Research* 8, no. 2 (2021): 41–48, https://journals.lww.com/iamr/fulltext/2021/08020/applications_of_artificial_intelligence_in.2.aspx.

30. Y. G. Chung, Y. Jeon, S. Yoo, H. Kim, and H. Hwang, "Big Data Analysis and Artificial Intelligence in Epilepsy - Common Data Model Analysis and Machine Learning-Based Seizure Detection and Forecasting," *Clinical and Experimental Pediatrics* 65, no. 6 (2022): 272–282, https://doi.org/10.3345/cep.2021.00766.

31. S. Yu, R. El Atrache, J. Tang, et al., "Artificial Intelligence-Enhanced Epileptic Seizure Detection by Wearables," *Epilepsia* 64, no. 12 (2023): 3213–3226, https://doi.org/10.1111/epi.17774.

32. G. L. Garner, D. R. Streetman, J. G. Fricker, et al., "Focal Cortical Dysplasia as a Cause of Epilepsy: The Current Evidence of Associated Genes and Future Therapeutic Treatments," *Interdisciplinary Neurosurgery* 30, no. 101635 (2022): 101635, https://doi.org/10.1016/j.inat.2022.101635.

33. H. Spitzer, M. Ripart, K. Whitaker, et al., "Interpretable Surface-Based Detection of Focal Cortical Dysplasias: A Multi-Centre Epilepsy Lesion Detection Study," *Brain* 145, no. 11 (2022): 3859–3871, https://doi.org/10.1093/brain/awac224.

34. K. Thai, K. H. Tsiandoulas, E. A. Stephenson, et al., "Perspectives of Youths on the Ethical Use of Artificial Intelligence in Health Care Research and Clinical Care," *JAMA Network Open* 6, no. 5 (2023): e2310659, https://doi.org/10.1001/jamanetworkopen.2023.10659.

35. A. C. Modi, S. M. Guilfoyle, K. A. Mann, and J. R. Rausch, "A Pilot Randomized Controlled Clinical Trial to Improve Antiepileptic Drug Adherence in Young Children With Epilepsy," *Epilepsia [Internet]* 57, no. 3 (2016): e69–75, https://doi.org/10.1111/epi.13289.

36. R. D. Bharath, R. Panda, J. Raj, et al., "Machine Learning Identifies "rsfMRI Epilepsy Networks" in Temporal Lobe Epilepsy," *European Radiology* 29, no. 7 (2019): 3496–3505, https://doi.org/10.1007/s00330-019-5997-2.

37. L. Kang, J. Chen, J. Huang, T. Zhang, and J. Xu, "Identifying Epilepsy Based on Machine-Learning Technique With Diffusion Kurtosis Tensor," *CNS Neuroscience & Therapeutics* 28, no. 3 (2022): 354–363, https://doi.org/10.1111/cns.13773.

38. A. van Westrhenen, R. H. C. Lazeron, J. P. van Dijk, F. S. S. Leijten, and R. D. Thijs, "Multimodal Nocturnal Seizure Detection in Children With Epilepsy: A Prospective, Multicenter, Long-Term, In-Home Trial," *Epilepsia* 64, no. 8 (2023): 2137–2152, https://doi.org/10.1111/epi.17654.

39. R. H. C. Lazeron, R. D. Thijs, J. Arends, et al., "Multimodal Nocturnal Seizure Detection: Do We Need to Adapt Algorithms for Children?," *Epilepsia Open* 7, no. 3 (2022): 406–413, https://doi.org/10.1002/epi4.12618.

40. S. Armand Larsen, D. Terney, T. Østerkjerhuus, et al., "Automated Detection of Nocturnal Motor Seizures Using an Audio-Video System," *Brain and Behavior* 12, no. 9 (2022): e2737, https://doi.org/10.1002/brb3.2737.

41. A. K. Tiwari, R. B. Pachori, V. Kanhangad, and B. K. Panigrahi, "Automated Diagnosis of Epilepsy Using Key-Point-Based Local Binary Pattern of EEG Signals," *IEEE Journal of Biomedical and Health Informatics* 21, no. 4 (2017): 888–896, https://ieeexplore.ieee.org/abstract/document/7508917/.

42. E. Kabir, S. Siuly, and Y. Zhang, "Epileptic Seizure Detection From EEG Signals Using Logistic Model Trees," *Brain Informatics* 3, no. 2 (2016): 93–100, https://doi.org/10.1007/s40708-015-0030-2.

43. J. J. Tharayil, S. Chiang, R. Moss, J. M. Stern, W. H. Theodore, and D. M. Goldenholz, "A Big Data Approach to the Development of Mixed-Effects Models for Seizure Count Data," *Epilepsia* 58, no. 5 (2017): 835–844, https://doi.org/10.1111/epi.13727.

44. S. M. Usman, M. Usman, and S. Fong, "Epileptic Seizures Prediction Using Machine Learning Methods," *Computational and Mathematical Methods in Medicine* 2017 (2017): 9074759, https://doi.org/10.1155/2017/9074759.

45. A. K. Jaiswal and H. Banka, "Epileptic Seizure Detection in EEG Signal Using Machine Learning Techniques," *Australasian Physical & Engineering Sciences in Medicine* 41, no. 1 (2018): 81–94, https://doi.org/10.1007/s13246-017-0610-y.

46. A. Subasi, J. Kevric, and M. Abdullah Canbaz, "Epileptic Seizure Detection Using Hybrid Machine Learning Methods," *Neural Computing and Applications* 31, no. 1 (2019): 317–325, https://doi.org/10.1007/s00521-017-3003-y.

47. N. Ilakiyaselvan, A. Nayeemulla Khan, and A. Shahina, "Deep Learning Approach to Detect Seizure Using Reconstructed Phase Space Images," *The Journal of Biomedical Research* 34, no. 3 (2020): 240–250, https://doi.org/10.7555/JBR.34.20190043.

48. Z. Brari and S. Belghith, "A Novel Machine Learning Approach for Epilepsy Diagnosis Using EEG Signals Based on Correlation Dimension," *IFAC-PapersOnLine* 54, no. 17 (2021): 7–11, https://doi.org/10.1016/j.ifacol.2021.11.018.

49. M. Natu, M. Bachute, S. Gite, K. Kotecha, and A. Vidyarthi, "Review on Epileptic Seizure Prediction: Machine Learning and Deep Learning Approaches," *Computational and Mathematical Methods in Medicine* 2022 (2022): 7751263, https://doi.org/10.1155/2022/7751263.

50. F. Onorati, G. Regalia, C. Caborni, et al., "Prospective Study of a Multimodal Convulsive Seizure Detection Wearable System on Pediatric and Adult Patients in the Epilepsy Monitoring Unit," *Frontiers in Neurology* 12 (2021): 724904, https://doi.org/10.3389/fneur.2021.724904.

51. G. Japaridze, D. Loeckx, T. Buckinx, et al., "Automated Detection of Absence Seizures Using a Wearable Electroencephalographic Device: A Phase 3 Validation Study and Feasibility of Automated Behavioural Testing," *Epilepsia [Internet]* 64, no. Suppl 4 (2023): S40–S46, https://doi.org/10.1111/epi.17200.

52. S. Beniczky, I. Conradsen, O. Henning, M. Fabricius, and P. Wolf, "Automated Real-Time Detection of Tonic-Clonic Seizures Using a Wearable EMG Device," *Neurology* 90, no. 5 (2018): 428, https://doi.org/10.1212/WNL.0000000000004893.

53. J. Arends, R. D. Thijs, T. Gutter, et al., "Multimodal Nocturnal Seizure Detection in a Residential Care Setting: A Long-Term Prospective Trial: A Long-Term Prospective Trial," *Neurology [Internet]* 91, no. 21 (2018): e2010–e2019, https://doi.org/10.1212/WNL.0000000000006545.

54. S. Beniczky, T. Polster, T. W. Kjaer, and H. Hjalgrim, "Detection of Generalized Tonic-Clonic Seizures by a Wireless Wrist Accelerometer: A Prospective, Multicenter Study," *Epilepsia* 54, no. 4 (2013): 58–61, https://doi.org/10.1111/epi.12120.

55. P. Keikhosrokiani, M. Isomursu, J. Uusimaa, and J. Kortelainen, "A Sustainable Artificial-Intelligence-Augmented Digital Care Pathway for Epilepsy: Automating Seizure Tracking Based on Electroencephalogram Data Using Artificial Intelligence," *Digital health* 10 (2024): 20552076241287356, https://doi.org/10.1177/20552076241287356.

56. K. Han, C. Liu, and D. Friedman, "Artificial Intelligence/Machine Learning for Epilepsy and Seizure Diagnosis," *Epilepsy & Behavior: E&B*

155, no. 109736 (2024): 109736, https://doi.org/10.1016/j.yebeh.2024.109736.

57. J. P. Leach, R. Lauder, A. Nicolson, and D. F. Smith, "Epilepsy in the UK: Misdiagnosis, Mistreatment, and Undertreatment?," *Seizure* 14, no. 7 (2005): 514–520, https://doi.org/10.1016/j.seizure.2005.08.008.

58. P. T. Cahill, M. A. Ferro, W. N. Campbell, and G. M. Ronen, "Self-Esteem Mediates Mental Health Outcomes in Young People With Epilepsy," *Epilepsia* 62, no. 9 (2021): 2072–2081, https://doi.org/10.1111/epi.17006.

59. S. Korkmaz, "Artificial Intelligence in Healthcare: A Revolutionary Ally or an Ethical Dilemma?," *Balkan Medical Journal* 41, no. 2 (2024): 87–88, https://doi.org/10.4274/balkanmedj.galenos.2024.2024-250124.

60. C. J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, "Key Challenges for Delivering Clinical Impact With Artificial Intelligence," *BMC Medicine* 17, no. 1 (2019): 195, https://doi.org/10.1186/s12916-019-1426-2.