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Radiology Section

Review Article

Role of Deep Learning in Neurodevelopmental Disorders: A Narrative Review

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ABSTRACT

The application of Deep Learning (DL) techniques in paediatric neuroimaging marks a significant milestone in the field. Using various DL methods, this study aims to provide a review of how these techniques can improve the diagnostic process for different neurodevelopmental conditions, including Attention Deficit Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD). The subsequent discussion addresses the prominent DL approaches applicable to paediatric neuroimaging and describes the key datasets that serve as the foundation of scientific research in this area. Additionally, the study highlights the limitations and shortcomings of these techniques, along with potential directions for future research and opportunities for further development. The adoption of these advanced methods has the potential to significantly improve patient outcomes, enhance diagnostic accuracy, and advance our understanding of early brain development.

Keywords: Attention deficit hyperactivity disorder, Autism spectrum disorder, Magnetic resonance imaging, Neuroimaging, Neurological conditions

INTRODUCTION

Neuroimaging plays a crucial role in the study of brain function, as it provides a modern, non invasive means to examine both the structural and functional aspects of the brain [1,2]. Neuroimaging methods enable highly detailed visualisation of brain activity and structures, contributing to a better understanding of how brain regions are involved in cognitive and behavioural functions such as perception, attention, memory, language processing, decision-making, and emotion regulation [3]. The paediatric brain differs significantly from the adult brain due to its distinct anatomical characteristics and rapid developmental changes in structure, metabolism, and function [4]. Diagnostic methods such as Electroencephalography (EEG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) are essential tools that facilitate timely clinical interventions [5].

Medical imaging is undergoing a transformation with the integration of Artificial Intelligence (AI), which is enhancing patient care and diagnostic precision [6]. AI has revolutionised imaging technology by improving accuracy in detecting abnormalities and enabling early treatment [6,7]. Among machine learning approaches, Deep Learning (DL) stands out for its use of artificial neural networks to process data efficiently. DL can extract complex features, detect subtle patterns, and identify biomarkers that may go unnoticed by human observers [5].

Early diagnosis and intervention are made possible by DL algorithms, which can analyse brain scans to detect abnormalities associated with ASD in children. DL also enhances diagnostic accuracy by recognising brain activity patterns linked to ADHD [5,7,8].

In this paper, authors review recent research on DL methods and their application in diagnosing neurodevelopmental disorders.

DISCUSSION

The articles reviewed were systematically sourced from the PubMed database. Publications from 2014 to 2025 were considered, using key terms such as “Deep Learning (DL),” “Autism Spectrum Disorder (ASD),” and “Attention Deficit Hyperactivity Disorder (ADHD).” Only articles with relevant abstracts and titles were included in the final review.

Advanced DL Methods for Neuroimaging Assessment

The DL has significantly transformed the processes of image analysis and classification through techniques such as Convolutional Neural Networks (CNNs), transfer learning, autoencoders, Linear Discriminant Analysis (LDA), and Generative Adversarial Networks (GANs) [8,9].

Convolutional Neural Networks (CNNs): CNNs have become an essential tool in medical image analysis and have revolutionised the field of computer vision [10,11]. They process images efficiently using structured data [5]. A typical CNN architecture comprises three main layers: the convolutional layer, the pooling layer, and the Fully Connected Layer (FCL). The convolutional layer serves as the fundamental building block of any CNN [12]. The number of convolutional layers should be optimised based on the specific task to achieve the best performance [5]. The pooling layer plays a crucial role in improving CNN performance by reducing dimensionality and focusing on the most important features [5,13]. The FCL connects every neuron in one layer to every neuron in the next, facilitating feature integration and classification [14]. A specialised CNN architecture, known as U-Net, has gained popularity for biomedical image segmentation, particularly in paediatric neuroimaging. It combines the strengths of CNNs with unique design elements that enable accurate and context-aware segmentation [15].

Transform learning technique: The transform learning approach integrates an encoder and a decoder while employing a self-attention mechanism [5]. This mechanism- also referred to as intra-attention- effectively connects different points within a sequence to determine its representation, thereby enhancing the model’s understanding of structural and contextual relationships [16].

Transfer learning technique: Transfer learning enhances the performance of paediatric neuroimaging tasks by leveraging features from models pre-trained on large datasets. It improves efficiency by using data from different but related tasks or domains, thereby reducing the cost and time required for training [17]. The process typically involves two stages: feature extraction and fine-tuning. Initially, the model is trained on a large neuroimaging dataset. For optimal results, the learned features are then incorporated into a new regression or classification model trained on the target dataset. Fine-tuning specific parameters for a particular task allows the model to adapt to the target domain, improving its predictive accuracy and ability to learn domain-specific features [18]. Transfer learning has made it possible for models to generalise across paediatric neuroimaging datasets. It is especially applicable when multicentre investigations must combine data from multiple sources [5,19].

Autoencoder: Autoencoders have been applied to several imaging tasks, including anomaly detection, dimensionality reduction, and image denoising. The encoder network maps input data into a lower-dimensional latent space, while the decoder reconstructs the original input from this representation. During reconstruction, the model learns to retain the most prominent features and structural information of the input data [20]. The Deep Stacked Denoising Autoencoder (DSDAE) is a robust denoising approach used for anomaly detection and localisation [21]. Several studies have demonstrated the potential of autoencoders in paediatric neuroimaging. For example, convolutional autoencoders have been used for dimensionality reduction of MRI data while preserving essential structural information. Additionally, autoencoders have been employed to identify brain abnormalities in MRI scans of premature newborns, successfully detecting atypical brain patterns [22].

Linear Discriminant Analysis (LDA): LDA is a powerful statistical method widely used across multiple fields [23]. It is a supervised classification technique that seeks a linear combination of features that maximises the separation between different classes within a dataset. By reducing high-dimensional data into a lower-dimensional space, LDA simplifies classification while maintaining class distinctions. This approach has proven valuable in improving the diagnostic performance of various neurological disorder studies by providing insights into patterns of neural activity and connectivity [5,24]. For instance, LDA has been used to distinguish between children with ASD and typically developing children based on activity or connectivity patterns in specific brain regions [25,26].

Generative Adversarial Networks (GANs): Generative Adversarial Networks (GANs) represent a revolutionary approach to generative modelling and unsupervised learning. Introduced by Ian Goodfellow and colleagues in 2014, GANs have transformed AI and have been widely applied in neuroimaging research [27,28]. In paediatric neuroimaging, GANs have shown promising potential in data augmentation [21], missing data imputation [29], and the generation of synthetic brain images [30,31]. A GAN consists of two neural networks- the generator (G) and the discriminator (D). The generator learns the distribution of the input data and produces realistic samples from random noise, while the discriminator evaluates these outputs, distinguishing between generated and real samples [27]. Through this adversarial process, GANs can generate artificial brain images that closely resemble real brain structures and activity patterns. By learning the underlying data distribution, GANs enable the creation of synthetic brain images for research, expand dataset diversity, and strengthen limited datasets for training [5].

Moreover, GANs are employed in image-to-image translation tasks, such as brain lesion segmentation and conversion of T1-weighted MRI images to T2-weighted images. Adversarial training ensures that the translated data remain true to the original while providing realistic, contextually coherent representations across imaging modalities [32]. [Table/Fig-1] summarises the application of various DL techniques [25,33-37].

DL technique	Application
CNN	Brain image segmentation, anomaly detection and classification of diverse types of tissues in the brain [33]
Transform learning	Enhancing the interpretability of complex brain imaging data and brain image segmentation [34]
Transfer learning	Image segmentation and enhancing the interpretability of complex brain imaging data [35]
Autoencoder	Anomaly detection, denoising images, and feature extraction [36]
LDA	Reduction of dimensions and classification of different brain states and disease conditions [25]
GAN	Synthetic MRI images, augment datasets, and improve image quality by removing noise and enhancing resolution [37]

[Table/Fig-1]: Application of different DL techniques [25,33-37].

Neurodevelopmental Disorders and Imaging Insights

a. DL-based neuroimaging for ASD

ASD is a neurodevelopmental condition that presents with a wide range of symptoms, from mild to severe. Difficulties in social communication and interaction often lead to challenges in interpreting non verbal cues, forming relationships, and expressing emotions. Individuals with ASD may also exhibit repetitive behaviours and restricted interests, such as repetitive movements or intense focus on specific objects [38]. MRI studies have revealed developmental abnormalities in the brains of young children exhibiting behavioural symptoms of ASD. These include alterations in temporal and frontal lobe development, amygdala volume reduction, and decreased total white and grey matter, all of which are more common in children with ASD compared to their neurotypical peers. Recent functional MRI (fMRI) studies further suggest that these neural differences provide valuable biomarkers for identifying ASD in infants and toddlers when compared to typically developing counterparts [39].

[Table/Fig-2] summarises DL techniques applied to neuroimaging for ASD across various imaging modalities [40-52].

b. DL - based neuroimaging for ADHD

ADHD is a prevalent neurodevelopmental disorder characterised by impulsivity, inattention, and hyperactivity. These symptoms can significantly impact a child's daily functioning and academic performance [53]. To distinguish individuals with ADHD from healthy controls, researchers employ multiple neuroimaging techniques that analyse features such as brain volume, metabolism, white matter connectivity, and functional activity. Key imaging modalities include conventional MRI, MR spectroscopy, volumetric MRI, Diffusion Tensor Imaging (DTI), functional MRI (fMRI), and voxel-based morphometry, all of which provide critical insights into the neurobiological characteristics of ADHD [54]. Furthermore, MR spectroscopy offers valuable information about brain metabolism, while fMRI effectively differentiates ADHD patients based on patterns of brain activity [55,56].

[Table/Fig-3] summarises DL techniques used for neuroimaging in ADHD across different imaging modalities [57-68].

c. DL based neuroimaging for other neurological conditions

Beyond ASD and ADHD, DL is increasingly being utilised to decode the neurobiological complexity of other paediatric neurological conditions- including epilepsy, cerebral palsy, and developmental dyslexia- through advanced neuroimaging and predictive modelling.

CNNs and Bidirectional Long Short-Term Memory (Bi-LSTM) networks applied to EEG and MRI data have facilitated early seizure detection, localisation of epileptogenic zones, and prediction of surgical outcomes in epilepsy. Similarly, DL models analysing infant movement videos and DTI scans have identified motor dysfunction in cerebral palsy before clinical symptoms appear. In developmental dyslexia, CNNs trained on fMRI and handwritten task data have revealed altered activation patterns in reading-related brain regions [69].

[Table/Fig-4] highlights the key DL techniques applied to neuroimaging in various other neurological disorders [70-77].

Dataset for Paediatric Neuroimaging

Diverse and extensive medical imaging datasets are driving a major transformation in paediatric neuroimaging. The Autism Brain Imaging Data Exchange (ABIDE) preprocessed datasets are essential

Author	Year of publication	Country of publication	Data from the imaging modality	DL model	Conclusion
Iidaka T [40]	2015	China	rsfMRI (resting state functional MRI)	Probabilistic Neural Network (PNN)	The researchers found that PNN achieved about 90% accuracy in classifying the two groups.
Li G et al., [41]	2018	China	MRI	Multichannel CNN	The multi-channel CNN method, combined with patch-level data expansion, showed strong potential for early ASD detection, enabling timely interventions and improved outcomes.
Aghdam MA et al., [42]	2019	Iran	fMRI	CNNs and transfer learning	The model demonstrated improved accuracy, sensitivity, and specificity over earlier studies on the Autism Brain Imaging Data Exchange (ABIDE) I dataset.
Xiao Z et al., [43]	2019	China	fMRI	CNN and Graph Neural Networks (GNN)	The study demonstrated impressive results, achieving an average diagnostic accuracy of 96.26%, along with a sensitivity of 98.03% and specificity of 93.62% while comparing school-aged children with ASD with typically developing individuals.
Sidhu G [44]	2019	Canada	fMRI	CNN	The classification accuracies have confidently exceeded 80% across multiple datasets.
Zhang D et al., [45]	2019	China	MRI	Dilated U net	This method effectively segmented small, low-contrast structures and correlated strongly with amygdala overdevelopment.
Ahmed MR et al., [46]	2020	China	fNIRS	Long Short-Term Memory (LSTM) and CNN	Achievement of 95.7% accuracy, 97.1% sensitivity, and 94.3% specificity, highlighting the promising potential of brain activity studies for ASD.
Xu L et al., [47]	2020	China	fNIRS	LSTM and CNN	The study demonstrated impressive classification accuracy, achieved a specificity of 94.3% and sensitivity of 97.1%
Yin L et al., [48]	2020	China	fNIRS	KAML (Kernel-based Additive Mixed Model Learning).	The KAML method clearly delivered significant enhancements in prediction accuracy.
Guo X et al., [49]	2022	China	MRI	CNN	Integrating conventional MRI and ADC data with DL algorithms offered a promising opportunity for the early and accurate diagnosis of ASD in children.
Saponaro S et al., [50]	2024	Italy	rs-fMRI and sMRI	Feature Dimensionality Reduction neural network (FR-NN) and CNN	Utilising the synergy of rs-fMRI and sMRI information, the multimodal joint fusion strategy exceeded the classification results produced with data gathered by a single MRI modality.
Ding Y et al., [51]	2024	China	fMRI	CNN and LSTM networks	DL techniques demonstrated satisfactory sensitivity, specificity, and Area Under the Curve (AUC) in ASD.
Sheik Abdullah A et al., [52]	2025	India	rs-fMRI	LSTM, Bidirectional Long Short-Term Memory (BiLSTM) and CNN	Demonstration of greater promise for diagnosing ASD, particularly in models that combined attention mechanisms with LSTM and BiLSTM networks.

[Table/Fig-2]: Definitive highlights of the DL techniques for neuroimaging in ASD [40-52].

Author	Year of publication	Country of publication	Data from imaging modality	DL techniques	Conclusion
Kuang D et al., [57]	2014	China	fMRI	Deep Belief Network (DBN)	DBN model demonstrated impressive capability in accurately discriminating ADHD.
Deshpande G et al., [58]	2015	USA	fMRI	Fully Connected Cascade Artificial Neural Network (FCC ANN)	FCC ANN achieved nearly 90% accuracy in distinguishing ADHD from healthy controls and around 95% in differentiating ADHD subtypes.
Hao AJ et al., [59]	2015	China	fMRI	DBN	DBN model effectively identified patterns associated with ADHD, demonstrating a high level of classification accuracy.
Chen H et al., [60]	2019	China	EEG	CNN	Results indicated an accuracy of approximately 90.29%, confirming the effectiveness of CNN for identifying ADHD.
Mao Z et al., [61]	2019	China	fMRI	Spatio-temporal DL method	Method utilising the public dataset from the ADHD-200 Consortium clearly surpassed traditional approaches, achieving an impressive accuracy of 71.3%.
Vahid A et al., [62]	2019	Germany	EEG	EEG Net	Model excelled in distinguishing ADHD patients from healthy controls, reaching a remarkable accuracy of up to 83%.
Dubreuil-Vall L et al., [63]	2020	USA	fMRI	CNN	Identification of key EEG features in ADHD patients, such as decreased alpha power and increased delta-theta power.

Riaz A et al., [64]	2020	UK	fMRI	Deep fMRI	Study underscored the vital role of functional connectivity in enhancing classification accuracy and delivered interpretable results.
Garcia-Argibay M et al., [65]	2023	Sweden	Registry data	Deep Neural Network (DNN)	DNN model demonstrated exceptional discriminative ability, positioning it as a powerful tool for improving decision-making.
Taspinar G and Ozkurt N [66]	2024	Turkey	rs-fMRI	CNNs and DNNs	The study emphasised the importance of examining all stages of the process, such as network and atlas selection, feature extraction, and feature selection, before classification.
Nouri A and Tabanfar Z [67]	2024	Iran	EEG	CNN and Layer-Wise Relevance Propagation (LRP)	The proposed method achieved a high accuracy of 94.52% in diagnosing ADHD.
Oyashi AS et al., [68]	2025	Bangladesh	rs-fMRI	Neural Network, Support Vector Machine (SVM), and a Random Forest classifier	The neural network, Random Forest classifier and SVM achieved an accuracy of 97%, 50% and 83%, respectively.

[Table/Fig-3]: Definitive highlights of DL techniques for neuroimaging in ADHD [57-68].

Author	Year of publication	Country of publication	Neurological conditions	Data from imaging modality	DL techniques	Conclusion
Ceschin R et al., [70]	2018	USA	Cerebellar dysplasia	sMRI (structural MRI)	3D CNN	Approach demonstrated considerable promise for the early identification of neurodevelopmental disorders.
Zhang J et al., [71]	2020	China	Conduct disorder	sMRI	3D CNN	3D CNN-based approach showed significant potential for classifying conduct disorder using structural MRI data.
Zahia S et al., [72]	2020	Spain	Developmental dyslexia	Task MRI	3D CNN	3D-CNNs accurately classified dyslexia using fMRI data, effectively distinguishing dyslexic individuals from non dyslexic individuals.
Attallah O et al., [73]	2020	Egypt	Embryonic neurodevelopmental disorder	sMRI	CNN	The approach demonstrated efficacy in identifying ends across a range of gestational ages and exhibited competitive performance relative to existing methods.
Menon SS et al., [74]	2021	USA	Disruptive behaviour disorder	sMRI, rsfMRI, Diffusion Tensor Imaging (DTI)	3D CNN	Results indicated that the proposed approach can effectively identify children with Disruptive Behaviour Disorders (DBDs).
Scheinost D et al., [75]	2023	USA	Cognitive and motor delays	Diffusion Tensor Imaging (DTI)	Recurrent Neural Networks (RNNs) and LSTMs	DL enabled predictive insights into brain development. While models like CNNs and RNNs showed promise in forecasting cognitive and motor outcomes, challenges in data consistency.
Alkhurayyif Y and Sait ARW [76]	2023	Saudi Arabia	Dyslexia	fMRI	CNN	The proposed model achieved an impressive accuracy of 98.9% and an F1-score of 99.0%.
Ortega-Leon A et al., [77]	2025	Spain	Cognitive deficits	fMRI	Multimodal data modal	The study highlighted the limitations of current approaches and underscores the importance of employing multimodal data models to improve early identification and intervention strategies for Neurodevelopmental Impairments (NDIs) in premature infants.

[Table/Fig-4]: Definitive highlights of DL techniques for neuroimaging in other neurological disorders [70-77]

resources for autism research, providing extensive neuroimaging data of subjects diagnosed with ASD. However, a significant limitation of ABIDE is the aggregation of data from multiple sites, which use different scanners, acquisition parameters, and include demographic variability. These site-specific effects introduce both linear and non linear confounds, which can obscure or mimic biological variations, leading to biased estimations and reduced reliability of results [78].

Participant recruitment within ABIDE datasets is often not diverse, with economic status, race, and ethnicity frequently underreported. This demographic homogeneity can prevent disadvantaged groups from benefiting from research and limits the generalisability of findings, potentially reinforcing preconceptions about brain–behaviour relationships [79,80]. Statistical biases, including inflated effect sizes due to multiple measurements, subjective reporting, and confounded parameters, can further affect neuroimaging studies using ABIDE. Even with a relatively large dataset, the limited number of cases at individual sites may reduce overall reliability [81,82].

ABIDE preprocessed datasets provide data that have undergone a sequence of predetermined processing steps. They are available for immediate analysis and include features such as connection matrices, ROI time series, and quality control metrics. Although ABIDE preprocessed datasets offer standardised and validated data, the choice of preprocessing methods can influence final results [83,84].

Similarly, the National Database for Autism Research (NDAR) is a large repository of neuroimaging and ancillary data, facilitating research on various aspects of autism [85]. However, differences in technology and data collection procedures across multiple sites introduce non biological variation, which can obscure or confound signals of interest. These site effects are often so strong that scans are best assigned to their original dataset, reflecting dataset-specific biases [86,87].

If not adequately controlled, variables such as sex, age, and brain size can render neuroimaging analyses inconclusive [82]. While NDAR contains a vast overall dataset, the limited number of cases in specific subgroups (e.g., particular ages, racial/ethnic populations, or individual traits) compromises the strength and generalisability of subgroup analyses [80,88].

As a premier resource for typically developing children and adolescents, the Paediatric Imaging, Neurocognition, and Genetics

Neurodevelopmental disorders	Datasets	Abbreviations	Study description	Data from imaging modality	Reference
ASD	ABIDE	Autism Brain Imaging Data Exchange (ABIDE)	Compiled structural and functional brain imaging data to enhance knowledge of the neural architecture	fMRI	[97]
	ABIDE Preprocessed	Autism Brain Imaging Data Exchange (ABIDE) Preprocessed	Data underwent processing by five distinct teams, each employing a range of effective tools.	fMRI	[98]
	NDAR	National Database for Autism Research	Offered neuroimaging data related to autism, focusing on its developmental aspects.	MRI, fMRI, PET	[85]
ADHD	PING	Paediatric Imaging, Neurocognition, and Genetics (PING)	Longitudinal study incorporating a range of neuroimaging data, with a specific focus on data related to ADHD.	Various neuroimaging	[89]
	ADHD-200	Attention-Deficit Hyperactivity Disorder -200	Multimodal MRI data analysis focussed on children diagnosed with ADHD in comparison to their typically developing peers.	Multimodal MRI	[92]

[Table/Fig-5]: Highlights of brain medical image datasets used for neurodevelopmental disorder [85,89,92,97,98].

(PING) initiative provides researchers with critical insights into normative brain development and cognitive maturation. However, as a multisite study, PING may introduce variability due to differences in scanners and imaging techniques. If not adequately standardised, these differences can complicate neuroimaging results. Being primarily cross-sectional, PING cannot establish causation regarding changes in the brain over time or developmental trajectories. Longitudinal data are needed to provide improved evidence of growth processes [89].

The size of connectomic studies is limited because some modalities, such as advanced white matter connectivity measures, were not originally incorporated or processed, despite PING furnishing dense multimodal data [90]. It is challenging to correlate neuroimaging results with intrinsic neurobiology, as imaging-based measurements cannot reliably reflect cellular or histological characteristics [91].

Additionally, the ADHD-200 dataset focuses on unique cerebral patterns associated with ADHD, providing a rich repository of neuroimaging data for researchers studying this disorder [92]. The Adolescent Brain Cognitive Development (ABCD) study substantially expands knowledge of brain development. Its large and heterogeneous dataset allows researchers to conduct comprehensive, long-term studies [93]. Although the ABCD panel was intended to reflect the US population on key socio-demographic measures, some subgroups were over- or underrepresented, limiting the generalisability of findings [93,94]. Large datasets also pose risks, including missing data and poor handling of missing information, which can distort results and reduce reproducibility [95]. Despite the richness of environmental and societal data in ABCD, additional data are needed to establish best practices for conducting valid research and accounting for structural and systemic biases, such as socio-economic health determinants and structural racism [96].

[Table/Fig-5] represents the major brain imaging datasets used for neurodevelopmental disorder research [85,89,92,97,98].

Challenges and Limitation(s)

One of the primary challenges in paediatric neuroimaging research is the limited availability of data compared to adult populations. Collecting data in children is ethically and logistically challenging due to low prevalence of certain conditions, parental consent requirements, and variability in developmental stages, age, and gender. Overcoming these challenges and developing robust DL models requires data-sharing platforms, collaborative research, and multicentre study designs [5].

The absence of standardised guidelines and protocols for DL in paediatric neuroimaging is another major limitation. Variations in preprocessing and imaging protocols create inconsistencies in data acquisition and analysis, which can only be addressed through uniform approaches. The lack of standard protocols also hampers comparability and reproducibility across studies, limiting the development of reliable and generalisable DL models. Therefore, the establishment of standard procedures is crucial to enhance the utility and reliability of research in this field [99].

Applying DL algorithms to paediatric neuroimaging also raises serious privacy and ethical concerns. The analysis of sensitive medical data must be conducted in strict accordance with ethical principles and legal requirements to maintain patient confidentiality [100,101].

DL algorithms can efficiently process large and complex datasets, uncovering hidden patterns in imaging data that may be overlooked by human observers. These algorithms can identify relationships between brain anatomy, functional properties, and responses to rehabilitation interventions, enabling the creation of highly personalised rehabilitation protocols tailored to each child's neurological profile. By optimising the use of therapeutic resources, such interventions can be both effective and efficient.

CONCLUSION(S)

DL has revolutionised paediatric neuroimaging by providing unprecedented precision and efficiency in identifying and treating neurodevelopmental disorders in children. Advanced technologies such as CNNs and GANs have significantly improved the detection of brain abnormalities, offering valuable insights into the anatomical and functional characteristics of the developing brain. Ultimately, the integration of these technologies into clinical practice has the potential to enhance the quality of care for paediatric patients, drive continued advancements, and ensure that these transformative tools are fully realised in healthcare settings.

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