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Abstract

Over the past decade, there has been a dramatic rise in the interest relating to application of artificial intelligence (AI) in radiology. Originally only ‘narrow’ AI tasks were possible; however, with increasing availability of data, teamed with ease of access to powerful computer processing capabilities, we are becoming more able to generate complex and nuanced prediction models and elaborate solutions for healthcare. Nevertheless, these AI models are not without their failings, and sometimes the intended use for these solutions may not lead to predictable impacts for patients, society or those working within the healthcare profession. In this article, we provide an overview of the latest opinions regarding AI ethics, bias, limitations, challenges and considerations that we should all contemplate in this exciting and expanding field, with a special attention to how this applies to the unique aspects of a paediatric population. By embracing AI technology and fostering a multidisciplinary approach, it is hoped that we can harness the power AI brings whilst minimising harm and ensuring a beneficial impact in radiology practice.

Keywords (separated by '-') Artificial intelligence - Machine learning - Radiology - Child

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The unintended consequences of artificial intelligence (AI) in paediatric radiology

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Abstract

Over the past decade, there has been a dramatic rise in the interest relating to application of artificial intelligence (AI) in radiology. Originally only 'narrow' AI tasks were possible; however, with increasing availability of data, teamed with ease of access to powerful computer processing capabilities, we are becoming more able to generate complex and nuanced prediction models and elaborate solutions for healthcare. Nevertheless, these AI models are not without their failings, and sometimes the intended use for these solutions may not lead to predictable impacts for patients, society or those working within the healthcare profession. In this article, we provide an overview of the latest opinions regarding AI ethics, bias, limitations, challenges and considerations that we should all contemplate in this exciting and expanding field, with a special attention to how this applies to the unique aspects of a paediatric population. By embracing AI technology and fostering a multidisciplinary approach, it is hoped that we can harness the power AI brings whilst minimising harm and ensuring a beneficial impact in radiology practice.

Keywords Artificial intelligence · Machine learning · Radiology · Child

Introduction

Despite the potential for addressing the significant pressures of increased service demand and staff shortages, the adoption and implementation of radiology artificial intelligence (AI) solutions into daily clinical practice remains challenging, with additional issues for paediatric radiology.

The reliability of AI-powered medical imaging depends on the accuracy and validity of the algorithms and quality assurance reviews to ensure they are safe and effective for patients, performing as intended and producing accurate, meaningful and where possible, explainable outputs. For the paediatric population, this evidence is less readily available than for adults. This may be partly due to reduced AI availability and thus adoption, complicated by additional hurdles for medical device regulations for use in children and less data available to help train reliable AI models.

A few recent surveys have alluded to some barriers to adoption. One conducted amongst paediatric radiology staff [1] found that lack of funding and available evidence-based outcomes were the greatest barriers. Another survey by the American College of Radiology (ACR) found that AI penetration in clinical practice was limited by concerns with inconsistent results, productivity and a lack of trust in the safety and efficacy of AI applications, with AI algorithms creating a 'black box effect' [2], meaning that it is unclear how specific AI algorithms have come to their conclusions. As a result, there are widespread calls for greater transparency and assurances around the use of AI in healthcare [3, 4].

Without such transparency and evidence, it is possible that the use of algorithms can lead to unintended consequences, both good and bad for patient care and radiology departments. In this article, we speculate how this may manifest based on real-world personal experiences, those reported in the literature and provide what the future may hold. A summary of our main points is provided in Table 1 and described in detail below.

AI algorithm use cases

Paediatric radiology has unique characteristics compared to adult radiology, including different physiological and developmental aspects, as well as distinct disease prevalence.

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Table 1 Summary of major aspects of unintended consequences for AI in paediatric radiology

Category	Explanation(s)
AI algorithm use cases	**Wasted resources** Early involvement of paediatric radiologists in model development is vital to ensure appropriate clinical problems are being solved rather than those where data is available **Inappropriate usage** AI tools that generate decisions (e.g. additional imaging) may lead to increased radiation exposure in children if used autonomously Some tools may be intentionally or inadvertently used to bypass expertise in paediatric radiology rather than used as an adjunct for decision-making (possibly as a cost-saving measure)
AI algorithm training: data and labels	**Bias** If AI tools are trained on adult data, they may not be applicable to use in children. Datasets should be generalisable to the population the AI will be used in, and include diverse patient backgrounds Correct data labels are also vital **Data & privacy** The use of large datasets may infringe on patient privacy; however, use of open-source, publicly available datasets may not represent the 'true population' and may be inappropriately labelled by non-experts
Algorithm testing (including external test datasets)	**Performance in the real world** Validation of the AI accuracy in a diverse dataset and ongoing post-implementation surveillance of AI performance is necessary to ensure stated performance matches what is expected. Many algorithms perform worse in real-world settings than expected from research publications
Workforce and staff: human–AI relationship	**Over-reliance & complacency** Less experienced radiologists will be more swayed by inaccurate AI results, which may affect paediatric radiology more given the greater workforce shortages **Workflow disruption** AI tools may disrupt current status quo and established workflows and care pathways. This could lead to staff resistance or feelings of job threat **Radiologist as a "spider in a web"** Confusion and conflicting models of how the radiologist sees their role with respect to AI. The expertise conceptualisation in the power/knowledge relationship of radiologists and AI can be thought of as parallel expertise, forward expertise, augmented expertise and/or collective expertise [70]
Ethics, acceptability, responsibility	**Accessibility & inequality** AI tools might only be available in well-funded hospitals, or poorly functioning AI tools (which are better than nothing) could be useful in developing countries. This raises issues of equity, fairness, differences in performance of tools for different populations **Regulation & liability** Lack of clarity regarding how responsibility is shared and who is liable for errors **Lack of transparency** "Black box" concept of how AI tools are coming to their decisions may mean lack of trust for the output or explanation provided

These factors require tailored approaches to imaging modalities and diagnostic tools. In paediatric radiology, for example there is an increased dependence on ultrasound and magnetic resonance imaging modalities due to concerns about radiation exposure in children. A number of these modalities present challenges for machine learning model development as they are observer-dependent or dynamic studies that require expertise to administer as well as interpret and are challenging to represent in a single view such as with a chest radiograph [5]. In the development of AI algorithms for paediatric radiology, the participation of paediatric and radiology experts is crucial and not always present. Paediatric radiologists participating in the early development of AI tools can ensure that the AI solutions being developed accurately address the specific and appropriate needs of paediatric patients and are tailored to the unique anatomy, physiology and pathology encountered [6, 7].

One consequence of developing AI solutions for paediatric radiology is the potential for wasted resources due to the pursuit of irrelevant or uncommon use cases. This has been a recurrent issue in broader radiology machine learning research, as exemplified by the discordance seen in COVID-19 diagnostic system publications validated in silico versus those that served a usable clinical role. A large systematic review analysed over two thousand AI model publications and found that none of them were adequate to serve a clinical

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role[8]. To avoid this problem, collaboration between AI developers, radiologists and paediatricians is essential to identify high-yield, high-impact use cases and prioritise the procurement of relevant data and the development of such solutions. It also highlights the need for research within this domain to follow standardised reporting guidelines to ensure sound research methodology and result in reproducibility [9].

A one-size-fits-all approach of combining AI algorithms from adult and paediatric radiology may (whilst helping to reduce wasted resources) lead to misdiagnoses, inappropriate treatment plans and increased risk for children due to differences in anatomy, physiology and disease manifestations between paediatric and adult populations—although there is insufficient evidence to know this for sure at present. A recent review of machine learning analysis tools for adult radiographs on paediatric scans resulted in a substantial performance reduction with patient age being a significant predictive factor for errors [10]. To address this issue, the development of customised algorithms specifically for paediatric populations or the complete testing of adult algorithms for paediatric use is necessary to ensure the safe and effective application of AI in paediatric radiology.

Transfer learning is a valuable method for adapting existing AI algorithms to the unique needs of children. Apart from transferring neural network weights from general computer vision tasks, existing models trained in adult populations can be fine-tuned for paediatric use cases. This makes use of the hierarchical feature extraction processes of neural networks with the underlying concept being that simpler imaging features will be common across a range of domains [11–14]. These baseline features are important to consider as using models that are more closely related to the finetuning domain will result in better discriminative performance and can even improve prediction interpretability [15, 16].

AI algorithm training—data and labels

AI training refers to the process of training a machine learning model to perform a specific task, such as image identification. This process involves feeding large amounts of data, i.e. radiology images (which are usually labelled—that is to say the pathology or abnormal finding on the image is annotated or assigned), into a learning model and then adjusting parameters of the model until it can accurately classify or generate new data. Several good articles that explain the process of data preparation and model training are available in the medical literature for those interested in learning this step in more detail [17–21].

Training data is largely locally sourced in a variety of centres. Given the need for a large number of cases, data is either limited to common anomalies or data from a large hospital. This immediately results in bias relating to ethnicity, especially when generalising to a global population. One well-known and interesting example is the misidentification of facial recognition AI in people of colour, as described by the US Department of Commerce [22]. This sampling bias is a result of training sets using a homogenous population of often male Caucasian data. To improve this issue of bias, it is necessary to clearly provide guidelines about creating responsible solutions [22].

With respect to imaging, a labelled dataset might include radiographic images of patients with and without tumours, where the correct output label (i.e. type of tumour being present) is provided alongside each image. This label may be generated by the subjective opinions of humans (rather than histopathological diagnosis if unavailable), and ideally by experts with an in-depth knowledge of the task at hand. The quality of the labels is crucial for the model. Expert opinion on a diagnosis can vary based on education, local practice, resources and treatment options at different institutions. Ideally, to appropriately label a dataset by expert opinion, it is advisable to have multiple people from different institutions give their input, or to use more objective outcome data as labels (e.g. mortality, repeated attendances, tumour cell type etc.). Where expert opinion is required, consensus within some of these parameters should be obtained. In a recent article by Wu et al. [23], image labels were first generated by one group of experts, then validated by eight others. This rigour allows for certain biases to be limited although the practicalities of doing this are challenging.

Open-source datasets (free, readily available data for public use without the need for ethical approvals) can be problematic as disease processes can be labelled differently in different datasets—for example “infiltrate” versus “consolidation” or “pneumonia” on chest radiographs, which have been used in publications [24]. This type of bias where a similar image is labelled inconsistently can result in lower accuracy of an algorithm trained on that particular dataset as it will find it difficult to determine differences between the labels for the same disease process and thus the output values may be varied for identical cases. There is therefore a critical need to facilitate multicentre paediatric consortia with infrastructure for secure data sharing and algorithm training and accurate labelling, including federated learning and cloud computing technologies [25, 26].

Finally, some researchers have considered identifying whether a pathology (e.g. fracture) is present on a radiograph by comparing it with a modality like CT or MRI acquired within a short follow-up timeframe as the ground truth. This creates the issue where an algorithm is being trained to visualise a pathology that may not be present on the radiograph and could decrease the actual utility in a real-life scenario. For example, if such an algorithm is implemented in real life and flags up a fracture that no one can identify on a radiograph, should the patient be sent for a CT or MRI even if

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there is no or low clinical indication on the off chance the AI algorithm can see something we cannot?

Building and training an AI model might be executed in several different ways, and the choice of the architecture of the AI model itself, as well as the choice of parameters, might differ depending on which combination of factors provides the highest accuracy rates. In general, models should be trained on datasets which are appropriately labelled and generalisable to a large population.

Algorithm testing (including external test datasets)

Testing (test set, test data) is the process of ensuring that an AI algorithm performs as intended, achieves accurate results in real life and can be trusted to make important clinical decisions. Without proper testing, AI algorithms may be used that are unknowingly producing inaccurate or biased results that can lead to misdiagnosis, delayed treatment, or even harm to patients. A systemic review by Yu et al. [27] of AI algorithms for image-based radiological diagnoses found that the vast majority of AI algorithms demonstrated diminished performance when tested on external datasets (i.e. a dataset not originating from the host institution(s)), with some reporting a substantial performance decrease. The generalisability of AI algorithms can only be proven by external test sets of various institutions and radiological equipment [27].

Whilst internal and external testing is required for regulatory compliance, there are currently no standard industry pathways to continuously monitor and test AI medical imaging solutions once deployed, and this is one major aspect that has been overlooked [9, 28]. The landscape is however quickly changing, especially in the UK, as seen by the recent guidelines updated in August 2022 by NICE [29]. The NICE evidence standards framework (ESF) for digital health technologies describes standards for the evidence that should be available or developed for digital health technologies to demonstrate their value in the UK health and social care system [29].

Peer review is another way to control and improve diagnostic quality where the AI analyses for some selected cases are scrutinised by human experts during the clinical workflow [30]. This approach can ensure that the algorithm is accurate and reliable before it is used in clinical settings, as well as detect any errors or biases that may arise in a real-world setting to allow for prompt corrective action.

During clinical use, the AI algorithm should be continuously monitored for accuracy, sensitivity, specificity and other relevant metrics. Any errors or biases that are identified should be promptly addressed, and the algorithm should be retrained if necessary to minimise this [31]. Real-time testing can also help identify new clinical scenarios where the AI algorithm may be useful or where it may need further development and what further training data may be required [32]. Despite being technically possible, continuously learning AI models should be avoided as negative feedback loops can result in impaired model performance.

Workforce and staff: human–AI relationship

Recently, AI has attracted unprecedented coverage in the media with particular scrutiny on the speed of its development and the potential risks it may have on society [33]. In March 2023, over 2000 prominent public figures and global influencers collaboratively requested there be a moratorium on AI technological development due to, what they quoted as, “laboratories being locked in an out-of-control race to develop and deploy ever more powerful digital minds that no one—not even their creators—can understand, predict, or reliably control” [33]. With such dramatic statements about AI technology in the public eye, it is imperative that AI development within healthcare is separated from this current global conflict, and the parameters for its integration into healthcare are clearly defined for each use case to negate public and staff scepticism. Where AI is useful and beneficial to healthcare (e.g. for areas of limited clinical knowledge and where specific paediatric radiology expertise is scarce [34]), it is important to nurture AI acceptability amongst patients and parents.

Nevertheless, we need to be aware of the AI-human interaction and in particular how inaccurate AI may cause potential harm [35]. Recently, Gaube et al. [36] assessed the behaviour of radiologists with respect to outputs from clinical decision aids. The authors found that radiologists across different levels of expertise often failed to dismiss inaccurate advice provided to them, regardless of whether this was provided by a human or AI. There was a general tendency amongst study participants to agree with the advice provided to them, particularly where they lacked their own experience. This observation has important implications. Less experienced radiologists are at greater risk to be influenced by inaccurate AI decision support tools by focusing on a specific diagnosis. Rather than establishing a pathway of cross-checking differential diagnoses, AI tools might stimulate confirmatory hypothesis testing, where radiologists orient their attention towards aspects of the images that align with the AI-suggested advice than looking at a broader picture. This is one unintended influence of AI on professional heuristics and an important potential pitfall within paediatric radiology, where experience may be limited or insufficient meaning a greater proportion of inexperienced users who fail to identify an inaccurate AI system.

The threat of AI algorithms replacing expert opinion in underserviced areas remains important. Even when AI has

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been implemented as a diagnostic aid as opposed to a formal diagnosis, clinicians and less experienced radiologists have a tendency to rely more heavily on AI interpretation, at times, contrary to expert opinion. This scenario can create distrust and reticence amongst paediatric radiologists regarding the implementation of AI systems—on the one hand for their inaccuracies and on the other hand as a potential job threat. This scenario can also mistakenly comfort non-experts in their capacity to interpret specialised imaging. For the moment, regular communication with clinical partners is important to explain and demonstrate the limitations of current AI solutions.

With regard to workforce impact, it is critical to define the target end users for various AI tools. Built-in AI improvements are designed to improve quality and efficiency in the radiology department, but may have untoward effects especially in untested paediatric populations. Radiologists and technologists may not be directly involved in these processes and will need to become familiar with potential pitfalls and errors. Other AI algorithms, such as preliminary reports and results communication, may be tailored towards the clinician or patient experience, and if the AI results differ from the radiologists' opinions, this could lead to dissatisfaction and distrust.

Metrics generated by AI software may also be used by referring physicians to make diagnoses or decide upon patient management. For instance, measurements of scoliosis angles can be automatically generated by AI with high reproducibility, reducing reporting time for radiologists and improving inter-observer agreement. However, many orthopaedic surgeons still prefer to make their own measurements, which directly relate to the decision to perform surgery. Therefore, referring physicians and families should also be involved in the evaluation and adoption of AI tools to provide broad perspectives on the benefits and risks of widespread adoption[37–40]. Radiologists, technologists and other staff will also need to be involved in decision-making processes to avoid feeling threatened by the perception of AI "replacing" them [41–43].

Ethics, acceptability, responsibility

AI in paediatric radiology brings up several ethical, legal and moral considerations, some already discussed above. In general, ethical considerations in AI include fairness and inclusivity, trust and transparency, privacy and security, reliability and safety, accountability and oversight and social and environmental well-being [44–50]. Several international radiology organisations have emphasised the need for human-centric algorithms that provide equal benefit for all, which is particularly important in the setting of vulnerable paediatric subjects [51–54].

Major classes of use cases for AI include improvements in workflow, image quality and image detection/interpretation. Many of these algorithms are already incorporated into commercial vendor equipment for adult applications. For example, smart scanners can assist with patient scheduling, appropriateness of imaging, automatic protocol selection, suggestion of appropriate position and scan ranges. Post-scanning, AI can also be used to reconstruct and denoise to improve image quality and detail. However, these algorithms may not perform as expected for children with small and immature anatomy, greater motion and anxiety and paediatric-specific dose reduction and image optimization. Paediatric patients can have complex and subtle findings, such as multisystem or congenital anomalies, that are not accounted for by traditional AI algorithms. Image filters can excessively alter data, creating artifacts that could be interpreted as abnormalities[55].

Explainability is an important issue in AI, given the "black-box" nature of deep learning networks. When AI produces an unexpected result and the underlying computational steps are not transparent, it becomes challenging for radiologists to identify and rationalise errors. As with other computational tools, radiologists should be able to provide oversight of AI solutions. However, they may feel awkward overriding a program that has reportedly seen many more images than they have. Therefore, basic training in the use of AI should be provided to radiology trainees and faculty [56–59].

The lack of standardised benchmarks in paediatric care also makes it difficult to compare various models with each other and with normal clinical practice. A model that performs at 70% accuracy for example would not be accepted in a dedicated children's hospital where higher standards are expected, yet could still be better than the status quo in an underserved area without access to any paediatric radiologists. This brings up issues of fairness and socioeconomic determinants of health, particularly if governmental agencies are responsible for regulating such technology. Some AI tools utilise novel quantitative metrics that cannot be replicated or validated in conventional clinical practice. This leads to questions of trustworthiness, and whether some practitioners can ethically choose not to use AI [60, 61].

Currently, a number of AI publications report performance similar to or better than humans, but only for narrow and simple tasks such as bone age estimation. Meanwhile, countless examples of failed AI go unreported. Publication bias towards encouraging results could lead to adverse effects, especially in vulnerable children. Nevertheless, as AI improves, it will be impossible to completely avoid the technology shift. Therefore, radiologists will need to find ways to leverage AI methods to help improve their overall clinical performance. Currently, the potential gain is greatest for accelerating mundane and repetitive tasks that can expend significant time and cognitive effort. For example, AI tools

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can help address first-line triage and protocol questions; provide preliminary “trainee-in-a-box” reports; and facilitate lesion detection, segmentation and comparison [62, 63].

Payment for AI services is also an important consideration. Current business models for AI include cloud-based, with remote hosting on vendor servers; and license-based, with on-premise installation on local servers. Pricing can be defined using quantity (number of imaging examinations), usage (total data used) or flat-rate (unlimited processing per billing cycle) models. Despite commercial market approval of multiple AI products, there are very few examples of insurance reimbursement for AI. In order to establish added value for government and insurance agencies, larger clinical trials and real-life observational studies are required to demonstrate how the additional information is actually used by clinicians, and how it impacts patient outcomes [64–69].

The question of responsibility for AI is a controversial one. It would be preferable for AI companies to guarantee model quality and generalizability. However, model performance is difficult to achieve and maintain over time without ongoing access to patient data, including a heterogeneous group of patient populations and imaging techniques. Furthermore, model designers in industry partners may not appreciate the wide range of clinical implications for the tools they develop. Radiologists, as model operators and key users of these technologies, should serve as the final arbiter of AI results[70]. Therefore, many groups have suggested that AI outputs should not be part of the official patient record in the PACS system or radiology report [71, 72].

In the future, it is possible that AI will begin to exceed human performance and reasoning for more complex tasks, such as the synthesis of multiple imaging findings to reach a specific diagnosis. There may come a point at which AI consistently outperforms humans and becomes the reference standard, such that the failure to utilise AI is considered negligent. As AI becomes more integrated into daily radiology practice, unintended bias, mistakes and malfunctions in AI tools will become more difficult to combat. This is a complex and evolving issue, which requires radiologists to continually engage with regulatory and legal agencies to prevent adverse effects and maximise positive impact[73–76]. Rather than perceiving AI as a threat, we should consider this an opportunity for humans and machines to collaborate and develop a hybrid superintelligence that optimises resource utilisation and patient impact [77–80].

Closing remarks

In conclusion, the development and implementation of AI algorithms in paediatric radiology should consider the unique aspects of paediatric patients, the importance of involving paediatric and radiology experts, population differences and disease prevalence and the risks of a one-size-fits-all approach to provide accurate, relevant, and safe diagnoses for children. There is a need to develop large, open paediatric imaging banks to provide more varied performance metrics to assess model generalisation and to augment transfer learning processes with the overall goal of developing systems that work across the paediatric populations. Proper testing methodology can help identify and address bias in the data or algorithm, and regular re-evaluation can help ensure that the algorithm remains accurate over time. With this in mind, it is hoped that unintended harm that may occur for paediatric patients can be minimised and the use of novel digital technology is implemented in a beneficial way for all. AQ6

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Declarations

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