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AI Applications in Pediatrics: Past, Present, and Future

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ABSTRACT

In pediatric medicine, Artificial Intelligence (AI) currently remains as a novel area for research and development. Most AI applications created for adults are often complicated to fully transfer over to pediatrics due to several limiting factors. These factors include physiological differences, lack of data, and unknown implications. Nevertheless, applications in adult medicine have influenced extensive reviews for algorithms that show significant potential in pediatrics. As pediatric data gradually increases, several AI algorithms for adults can be fine-tuned to provide similar accuracies and sensitivities for diagnosing specific pediatric diseases. This chapter will discuss the pioneering applications of AI in medicine as well as current and arising applications or subspecialties. Areas of discussion encompass precision medicine, oncology, cardiology, radiology, chatbots, neurology, and ophthalmology. AI algorithms within these domains range from assistance with diagnoses, shorter waiting times, to continuous monitoring. Common benefits exhibited by many applications include increased accuracy, time and cost efficiency, patient compliance, and flexibility. For example, medical wearable technology and chatbots are two AI applications that can provide certain patient care in both outpatient and inpatient settings. These algorithms are convenient to use and offer continuous monitoring when a provider may not be readily available. Furthermore, other topics explored in this chapter relate to common concerns for using AI in pediatric medicine and education for health professionals, parents, and children. Most apprehension pertains to the misuse of data and quality of care. Reviewing these concerns is crucial for AI to exponentially flourish in medicine. Without established comprehension, hesitance and distrust may prevail over the promising potential AI can offer. Education and training can help alleviate these common misunderstandings by explaining how AI can affect both medicine and health care. Moreover, learning environments can allow health professionals, parents, and children to openly communicate their concerns that could guide ethical frameworks for developing AI applications. Analyzing these past, present, future applications, and related concerns can help demonstrate how AI will transform pediatric medicine.

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Introduction

Artificial Intelligence (AI) in pediatrics is gradually expanding as novel algorithms create beneficial opportunities for children, parents, and health professionals. Though more applications exist for adult medicine, numerous AI applications provide similar and unique assistance for pediatrics. Several representative applications that encompass both adults and pediatrics include voice dictation and electronic health databases. Voice dictation allows health professionals to create efficient clinical notes while electronic health databases are platforms where providers and patients can easily access medical information. These applications have been proven successful through the unparalleled influence they exude in healthcare settings. Algorithms for providing personalized treatment or precision medicine have also become eminent. These models assist with decision-making through extensive amounts of data. Broad data for children is necessary for highly accurate treatment plans yet current stored data remains minute. Nonetheless, there is substantial potential but entails the approval of parents and ethicists. Issues regarding ethics and children's safety naturally surround data utilization and algorithm development. Possible complications and concerns must be studied and addressed by researchers and designers for any AI application. Health professionals and parents should also be properly informed of how data and AI algorithms are implemented. Through understanding implications and limits that surround AI applications, assessing AI's practicality in pediatrics can be efficiently executed.

Early Practices of Artificial Intelligence in Medicine

AI in medicine was initially attempted in the 1960s and primarily concentrated on diagnosis and therapy [1]. The MYCIN system developed by Shortliffe from Stanford University is a pioneering work for the beginning of AI development. MYCIN was an expert system that utilized questions and rules to identify bacteria and generate antibiotic recommendations. This system was not clinically implemented; nevertheless, its outputs strongly compared to infectious disease experts and influenced pivotal aspects of AI. Voice dictation or voice recognition is another early application of AI in health care. Speech recognition specialists Dr. James and Janet Baker created Dragon Systems in 1982 that served as the foundation for voice recognition software. This software has transformed into Nuance, which is a common software utilized in many healthcare settings. The system offers health professionals the convenience and flexibility to create notes accurately and efficiently. Voice dictation remains prevalent in pediatrics since the terminology is generally analogous for both children and adults.

Artificial intelligence in medicine is predominately classified into two main categories—virtual and physical. Virtual includes health databases, electronic health records (EHRs), and algorithms that assist physicians with decision-making whereas physical consists of robotic technology that assists surgeons, such as the da Vinci surgery system [2]. This surgery system was inspired by Leonardo da Vinci due to his robot drawings from the 15th century. da Vinci surgical systems were approved by the FDA in 2000 and have been a leading approach for intricate, minimally invasive surgeries. These operations include hysterectomies, prostatectomies, gastrointestinal procedures like cholecystectomies and liver resections, and many more.

Current AI Applications in Pediatrics

Besides the previously established applications, many AI algorithms and applications have been created to support precision and personalized medicine. Precision medicine encompasses many common conditions and continues to incorporate more through emerging precision medicine programs. Numerous applications also assist health professionals and patients in diverse subspecialties by enhancing accurate, specialized care and prevention. Many current applications are designated to assist the clinician and their diagnoses rather than replacing their practicing role.

Precision Medicine

AI algorithms like machine learning (ML) and deep learning (DL) strengthen precision medicine through efficiently matching and organizing patients with similar genomic and clinical factors. Although the data is limited, artificial intelligence can be utilized to help providers diagnose and recommend treatments for children with similar environments and clinical factors. Diagnosing certain conditions in pediatrics such as severe asthma, cancer, and inflammatory bowel disorder have been enhanced by AI and precision medicine.

Pediatric Asthma

For children with severe asthma, controlling the condition is difficult and often results in a low quality of life [3,4]. Difficulties mainly stem from the incomparable treatments between children and adults, and challenges associated with using pediatric data. Varying mechanisms of severe pediatric asthma are also not fully understood and conducting diagnoses is complex [5]. Pediatricians may misdiagnose the patient with another common diagnosis such as pneumonia or bronchitis. The average diagnosis accuracy of pediatric asthma by pediatricians in all healthcare settings was ~59%, where primary care illustrated less accuracy compared to hospitals [6,7]. In an outpatient setting in the Children's Hospital in Zhejiang University School of Medicine, a questionnaire-based interface was implemented for assessing asthma in children pre- and postdiagnosis and follow-ups [6]. This system is convenient since it can be accessed through the smartphone and offers flexibility for the parents and children. Moreover, utilizing the data obtained from this interface can contribute to precision medicine and ultimately reduce the misuse of antibiotics and systemic glucocorticoids [6].

Pediatric Oncology

Precision medicine in pediatric oncology is significantly crucial since the genes associated with pediatric cancers vary in mutations and amino acid sequences [8]. Numerous pediatric cancers also illustrate the absence of reliable biomarkers and dissimilar tumor etiology compared to adults [9]. These complexities have inspired the development of precision medicine initiatives and programs in pediatrics. Maintaining these programs will strongly require diverse groups in healthcare—pharmaceutical companies, providers, researchers, designers, parents, and children-to collaborate. Moreover, pediatric cancers even with their complexities require common therapies such as chemotherapeutic agents, immunotherapy, radiation, and surgical operations [9,10]. These treatments are generally personalized and depend on age, risk, and type of cancer. Much research has been conducted for diagnosing staging and prognosis, but research surrounding targeted therapies and their complications remains limited [11, 12]. Nonetheless, these limited studies have created remarkable potential for evaluating pediatric cancers and possible treatments. For example, precision medicine trials such as umbrella and basket trials have helped discover appropriate treatments and gene variants associated with certain oncological diagnoses. These trials have strengthened precision medicine, especially for newly diagnosed patients. Some trials have been conducted for these patients with acute lymphoblastic leukemia (ALL) through utilizing leukemia samples for identifying Ph-like expression and its related variants [13]. Targeted therapies have also been determined through these successful trials, but more post-treatment complications should be monitored and recorded for patients with varying survival rates [12].

Pediatric Inflammatory Bowel Disease

Inflammatory bowel disease (IBD) is a chronic condition that affects the gastrointestinal tract and is prevalent locally and globally [13,14]. This disease is classified into four categories: Emergence, Acceleration in Incidence, Compounding Prevalence, and Prevalence Equilibrium, where both industrialized and developing countries are facing an increase in cases [14]. This increase comprises more of children and adolescents rather than adults. Therefore, providing appropriate therapies for this chronic condition during childhood is critical to enhance their quality of life. Precision medicine is suitable for assisting IBD since the RIGHT principles can be applied: Right Patient, Right Therapy, Right Dose, Right Time, and Right Strategy [15]. Moreover, precision medicine can be utilized for preventative measures for children at high-risk. A study conducted by Choung et al. signified that Crohn's disease can be predicted by serologically testing microbial markers and antibodies [16]. PREDICTS (Proteomic Evaluation and Discovery in an IBD Cohort of Tri-service Subjects) is the official name of the study and illustrated that CD-associated anti-microbial antibodies can be utilized to monitor Crohn's disease during and after diagnosis [16]. Recording these antibodies, phenotypes, and overall progression from these patients will help pediatric patients prone to IBD.

Pediatric Cardiology

Pediatric cardiology is a complex subspecialty that requires extensive screening and decision-making. Several common conditions found in cardiology include pediatric and adult congenital heart disease (CHD), myocarditis, and arrhythmias. CHD is a global issue and affects approximately 9 out of 1,000 live births [17]. This condition requires several screening tools, generally non-invasive, such as cardiac auscultation, pulse oximetry, and cardiac imaging [18]. CHD and other cardiac diseases can be identified and monitored with the assistance of AI through enhancing cardiac imaging, echocardiograms, and medical wearables.

Cardiac Magnetic Resonance Imaging

Cardiac magnetic resonance imaging (CMR) can be slow with long wait times. Several techniques have been implemented to lessen waiting times such as parallel imaging and compressed sensing [18]. AI has helped these techniques through de-noising and de-aliasing data and has increased accuracy through reduced errors [18]. Moreover, convolutional neural networks (CNN) created by Hauptmann et al. reduced CMR acquisition time to around 18 s [19]. These CNNs were applied to approximately 12 slices for 10 patients. Reduced acquisition times is especially beneficial for pediatric patients since many struggles with holding their breath. Infants and toddlers also encounter more issues since they naturally have raised vital signs [20]. Due to these common complications, many pediatric patients require anesthesia [21]. Anesthetizing the patient can assist patient cooperation but may make the overall process longer. Therefore, having reduced acquisition times would lessen the need for anesthesia.

Echocardiography

The potential of AI in pediatric echocardiography is promising and can be recognized through recent applications. Like cardiac MRI, echocardiograms are a diagnostic tool for CHD. Accurate echocardiograms depend heavily on the operator, but images can be automated and enhanced by AI. Fetal intelligent navigation echocardiography (FINE) is a system that uses spatiotemporal image correlation (STIC) to assist with the prenatal diagnosis of CHD [22]. STIC is relatively new and analyzes images after they are obtained. In a study by Chen et al., they reviewed how FINE could assist inexperienced and experienced operators compared to traditional echocardiography. Their study illustrated that the diagnostic accuracies using FINE was 81.66% for inexperienced and 87.50% for experienced operators, whereas for traditional the accuracies respectively were 16.66% and 84.16% [22]. These results are significantly different and illustrate that FINE is beneficial for novel operators in determining prenatal diagnoses for CHD. Another prominent AI application relates to the detection of cardiac structures and anomalies. Komatsu et al. created a CNN, Supervised Object detection with Normal data Only (SONO), that could recognize fetal cardiac substructures and unique abnormalities [23]. 363 pregnant women were examined, and fetal ultrasound videos were recorded. SONO was trained by select videos and the mean average precision of locating substructures was 0.70 and abnormality scores were appropriate for detecting anomalies, including CHD [23]. Results from both studies show that FINE and SONO are crucial applications that offers advantageous advances for pediatric echocardiography.

Medical Wearables

Many current medical wearable technologies exist alongside everyday accessories. Medical wearables are highly convenient since they can measure patient's vitals, such as heart and respiratory rate, in outpatient settings. One popular device is the Apple Watch that can detect abnormal heart rhythms like atrial fibrillation. Users receive a notification when an irregular pulse is identified by the 12-lead electrocardiogram embedded in the smartwatch. Information recorded in the Apple Watch and other medical wearables can also be shared with the patient's provider. Thus, these technologies provide continuous monitoring and flexibility for providers, parents, and pediatric patients. Wearable technology can also be helpful for children with CHD, which could prevent possible complications through early detection. This technology will most likely continue to thrive within the pediatric population since they are more inclined to trial novel technology [24, 25].

Pediatric Radiology

General radiology contains the most successful and clinically implemented AI applications compared to other specialties. Many of these AI applications assist the radiologist by improving image quality and detection. Medical AI systems are generally categorized into three classifications: AI-assist, AI-replace, and AI-extend [26]. AI-assist systems are more common compared to AI-replace, suggesting the role of clinicians cannot yet be replaced. In pediatric radiology, few applications have been clinically implemented, but many developed and tested algorithms show potential. Clinically implemented and favorably successful algorithms include assessing bone age, de-noising scans, and detecting pneumonia.

Bone Age

Bone age assessment involves measuring the maturity of a child's bone through hand and wrist radiographs or X-rays [26]. After the radiographs are obtained, they are compared to standard radiographs relative to the child's age and development. Currently, BoneXpert is the prominent clinically implemented tool on the market. BoneXpert utilizes the Greulich and Pyle and Tanner and Whitehouse methods and assesses radiographs in less than 15 seconds [27]. The quick scan time allows numerous images to be assessed, thus saving radiologists time and effort. BoneXpert can act as an AI-replace, AI-assist, or AI-extend. Generally, it is utilized as AI-assist but its capability as an AI-extend also calculates bone health index. Moreover, this tool is highly efficient and measures mostly all bones in the hand and wrist. It is also capable of dismissing bones outside of a particular region or beyond certain thresholds. Thresholds are set depending on the child's age; for children older than 7 years old, it is 2.4 years, and gradually decreases to 1.2 years for newborns [26]. BoneXpert will also disregard the scan if not enough bones are detected to prevent error. Overall, BoneXpert is a beneficial tool that assists many radiologists and remains important for assessing the bone age and unique development of pediatric patients.

Image De-Noising and Pneumonia Detection

Computed tomography (CT) is a vital tool for diagnosing pediatric conditions and can significantly be enhanced by AI. A common disease in pediatrics that CT scans can help assess is pneumonia. Pneumonia affects the lungs and can be severe and life-threatening if not properly treated. CT scans can reveal these extremities and other potential emergencies. For example, this imaging tool was proven critical for diagnosing both symptomatic and asymptomatic pneumonia, and associated issues in pediatric patients during the COVID-19 pandemic [28]. Although CT is a helpful tool, several concerns surround the constant utilization of CT in children, such as radiation exposure and compliance. Radiation exposure is an increasing concern for CT since this modality requires more radiation compared to traditional chest x-rays or radiographs. Studies have shown that radiation—both low-dose and high-dose-exposes children to increased cancer and tumor risks [29, 30]. Patient compliance is another issue if the child is uncomfortable and wary of the procedure. This can affect the quality of the scans and could potentially require repeat scans and subsequently, more radiation exposure. One method to enhance the efficiency of CT scans is through improving image quality. In a study conducted by Brendlin et al, an AI algorithm PixelShine created by AlgoMedica was utilized to determine its denoising ability for pediatric ultra-low-dose CT scans in 100 pediatric patients [31]. This algorithm denoises the scans after they are obtained and helps reduce diagnosis time. After the images were denoised, they were compared to standard weighted filtered back projection (wFBP), iterative reconstruction (ADMIRE 2), and PixelShine datasets. The results illustrated that wFBP datasets had the longest diagnosis time of 2.66 ± 2.31 min while PixelShine had the least of 2.28 ± 1.56 min [31]. The noise detected in PixelShine was also the smallest: 34.8 ± 3.27 Hounsfield Units

[31]. These denoising results from Brendlin et al. demonstrate that AI denoising algorithms are favorable for pediatric CT scans.

Chest radiography is another diagnostic tool utilized to detect pneumonia, pulmonary tuberculosis, and other abnormalities. Both CT and chest radiographs are excellent screening tools that are being gradually improved by AI algorithms. Though CT scans offer more detailed analyses, chest radiographs can serve as alternatives that offer less radiation exposure. In a study by Tang et al., they utilized a CNN to help assess pulmonary conditions on chest radiographs [32]. The CNN had a training set of approximately 8500 images and focused on both adult and pediatric patients. The area under the curve (AUC) in pediatric patients was ~0.98 for classifying normal and pneumonia detected radiographs [32]. Other established studies for assisting pneumonia diagnosis includes the Guangzhou Women and Children's Medical Center (GWCMC) dataset and Pneumonia Etiology Research for Child Health (PERCH) dataset. The GWCMC dataset focused on labeling chest radiographs for three types of pneumonia: normal, bacterial, and viral [33]. The PERCH dataset focused on studying severe cases of childhood pneumonia that required hospitalization. This data transpired from 7 countries-Bangladesh, Gambia, Kenya, Mali, South Africa, Thailand, and Zambia-through the World Health Organization [34]. For pulmonary tuberculosis, CAD4TB is a current software that can efficiently analyze this condition in children. It is also cost-efficient and has high sensitivity which can be beneficial for any clinical setting.

Arising AI Applications and Subspecialties

Numerous AI algorithms in diverse fields show compelling potential in pediatric clinical settings. Since AI is a novel concept in medicine-especially pediatrics-clinically implemented applications are currently limited and scarce. However, numerous algorithms are being developed and reviewed through various studies. Many incorporate the overall well-being of the pediatric patient as well as ethical frameworks that must be followed and respected. Some arising applications and progressing fields include chatbots, neurology, and ophthalmology.

Chatbots

Chatbots are flexible messaging systems that can be utilized in both outpatient and inpatient settings. Chatbots are designed to incorporate a child's mental, physical, and physiological well-being and utilizes everyday language for natural communication. Since these messaging systems can be highly specific, they can contribute to personalized medicine and certain conditions. For example, a novel chatbot has been developed for pediatric obesity. Pediatric obesity is becoming an increasing concern in pediatrics and addressing the issue may initially be difficult for parents and children. Tess is a behavioral coaching chatbot available 24/7 that focuses on addressing weight management, anxiety, and depression [35]. Stephens et al. analyzed how adolescents engaged with Tess and 81% had positive progress while 96% of the exchanged messages were helpful [35]. In the future, chatbots can be implemented for other globally prevalent conditions. Moreover, it is important to note concerns that may arise during development and implementation. Chatbots are personalized and become more confidential as the child inputs more information [36]. The information must remain protected and chatbots should be holistically developed to prevent any misinterpretation or disclosure. To ensure chatbots run properly, these applications should also be analyzed and reviewed by health care professionals.

Pediatric Neurology

The field of pediatric neurology includes both common and rare conditions that require extensive screening for proper medical treatment. Diagnoses within neurology are naturally complex but assistance with precision medicine and AI algorithms show immense potential. There is currently no routine clinically implemented applications in neurology, but many studies are being conducted with potential contribution for implementation. Two conditions that have been studied are pediatric concussion and brain tumors.

Concussion

Concussion, or mild traumatic brain injury (mTBI), is considered common and most general genre of traumatic brain injury [37]. It involves any changes to brain activity and is defined as having one of the following symptoms: memory loss prior or after event, fainting, change in mental state, and focal neurological deficits [38, 39]. mBTIs are also recognized by biomarkers in the brain which can also be difficult since pediatric biomarkers typically differ from adults. Children and adolescents are most prone to mBTIs, which mostly occur from extracurricular activities like sports. Generally, these activities are supervised by non-health care professionals and can lead to decreased numbers of diagnoses [37]. This could be problematic if the concussion is not properly diagnosed and leads to future issues. Since concussions do not always involve syncope, this also contributes to the absence of pediatric concussion recognition [37]. In a study by Bahado-Singh et al., they utilized AI to measure blood DNA cytosine (CpG) methylation markers and other clinical predictors to diagnose mTBI. They used deep learning to analyze 449 CpG sites or 473 genes, and sensitivity and specificity was □95% [37]. The results indicate that epigenetic marker detection through AI has potential success for predicting mTBIs.

Brain Tumors

Brain tumors are the most prevalent solid tumors in pediatrics [40]. Brain cancer is also the most common cancer-causing death in pediatric patients, which replaced leukemia during the years of 1999-2014 [41]. Prognosis for brain cancer and tumors remains poor but novel approaches for treatment-including AI-are being developed. Huang et al. reviewed various studies where AI can be implemented for diagnosis, in which pediatric brain tumor imaging was the most common [42]. Out of the 6 studies they reviewed, 5 of them were considered sufficient for tumor diagnosis. Moreover, brain and tumor segmentation is a crucial aspect for diagnosing and monitoring brain tumors. This concept for pediatrics is highly limited but data from adults can help guide development. Drai et al. conducted a study to explore this transferability of utilizing AI for brain (HD-BET) and tumor segmentation (HD-GLIOMA) [43]. They found that HD-BET was efficient for pediatric brains and HD-GLIOMA is decent for tumors with contrast. In coming years, AI can be implemented to help routine checkups run more efficiently while saving the clinician's time, allowing them to provide more holistic care.

Pediatric Ophthalmology

Studies for AI applications in pediatric ophthalmology is limited yet require more attention as monitoring eye development in children and adolescents is vital for their quality of life. Moreover, the studies remain limited since the common conditions encountered in adults significantly differs than those in pediatrics. For example, widespread diseases in children include congenital eye diseases, nasolacrimal duct obstruction, and retinopathy of prematurity (ROP), whereas in adults it is cataracts, glaucoma, and macular degeneration [44]. Congenital eye diseases can also differ significantly than those same diseases encountered as an adult.

AI applications for this subspecialty will be extremely beneficial, especially when communication and patient compliance can often be an obstacle during examinations. Multiple visits are often necessary since little information is obtained due to limited communication and developmental skills [44]. Children may easily lose attention and get distracted; thus, necessitating providers to conduct quick appointments [44]. Several advances have been conducted to help evaluate pediatric ophthalmic conditions. The most studied is retinopathy of prematurity (ROP) which is considered one of the leading causes for childhood blindness [44,45]. Variability is prevalent during ROP diagnosis, making it highly subjective and requiring multiple examinations [46]. AI has been applied to assist this process through analyzing and determining the grading through fundus photos [44]. This assists the clinician by rendering it less subjective by comparing the patients' imaging with standards. Additional data and outputs can be utilized to strengthen the success of this algorithm. Incorporating AI within ophthalmic practice will be more efficient for the provider and patient.

Concerns in Pediatrics

AI implementation in pediatrics encompasses issues and concerns that are both analogous and dissimilar to adults. The general concern for ethics remains prevalent in pediatrics, specifically where future risks or complications are unknown. It is truly important to follow an ethical framework for developing AI programs to alleviate this concern. Similar topics regarding data protection and privacy should also be addressed to ensure minimal misinterpretations. This should be addressed by those involved in developing and maintaining an AI application such as researchers, designers, and health professionals. Providers are also responsible for communicating with the parents or guardians to guide them with proper informed consent and decision-making.

Misuse vs. Use of Data

One major ethical concern in pediatrics is the utilization of data. This topic remains controversial as various voices discuss how data should truly be implemented. Clinical data is considered raw data that can be utilized to help people understand how diseases occur and its possible treatments [47]. Data can be reviewed for research and development to provide advancements globally. For this purpose, data should not be misused and must be handled properly while protecting those who are involved. Clinical data should be used beneficially to create a positive impact, making this a moral obligation of those involved in the health care system [47].

Decision-Making as a Parent

Parents are the primary determining factor for children's health care since they are responsible for consent and decision-making. As AI gradually becomes more incorporated in medicine, concerns naturally arise and acceptance towards these changes can be difficult for parents. In a study conducted by Sisk et al., they measured parents' openness and concerns towards AI in pediatric medicine [48]. They recorded responses through a survey then analyzed mean values. The mean openness score for the test they created was 3.4 on a scale of 5, where 1 was "not at all open" and 5 was "extremely open" [48]. This mean indicated people are slightly more inclined to AI in medicine yet are wary of certain implications. Most concerns corresponded with openness and social determinants of health. The associated concerns were social justice, quality, cost, and convenience. Social justice is a crucial concern yet ambiguous since the outcomes of AI applications are often not immediately visible. Novel AI technologies also raises apprehension for quality, convenience, and cost since these factors cannot be appropriately measured until the algorithms are implemented.

In another survey, conducted by Ramgopal et al., they designed a fake scenario where they asked parents if they would allow their child with a respiratory illness to receive medical treatment assisted with AI. The purpose of this study was to identify parental concerns and which populations were open to AI implementation. Most concerns correlated with misdiagnoses (63%), inaccurate treatment (58.9%), and clinician inattention (57%) [49]. Their results also illustrated that Black (Non-Hispanic) parents illustrated more discomfort towards AI compared to White (Non-Hispanic) parents [49]. Both surveys and studies contribute to the factors that researchers, designers, and ethicists should consider when developing an AI algorithm. It also illuminates the importance of including parents and children as parties who should heavily influence AI models.

Educating Academic and Clinical Health Professionals

Both academic and clinical health professionals must receive proper education and/or training for AI to efficiently succeed in medicine. During this process, health professionals should also begin to adapt and trust the transformations AI will offer in years to come. They must focus on ethical considerations surrounding AI applications and should concentrate on providing safe and effective care to their patients. Providers are responsible for explaining how the application functions as well as potential complications and risks to the parents and pediatric patients. Moreover, understanding how an AI algorithm functions as a provider is crucial for parents to give proper informed consent. Lack of this understanding will engender increased misunderstandings if the provider cannot explain why the prediction was accurate or faulty [50]. Subsequently, it would alter the validity of the provider's ability to present thorough information. Through necessary education and training, researchers and health professionals must protect pediatric patients while providing optimal care and maintaining interpersonal relationships.

Preserving Interpersonal Connections

A common apprehension towards AI is the diminished connection between a provider, patient, and family. Many perceive a gap growing between relationships with the increasing amount of AI applications. Traditional interactions like in-person appointments and documentation have shifted to online modalities. Online technology is convenient and flexible for both the provider and patient. However, it can naturally cause disconnections, especially if one's appointment and concerns are conducted through brief appointments or a messaging software. This illustrates that AI can potentially depersonalize and alter interpersonal relationships through decreased in-person social interactions [51]. Provider-patient relationships are often strengthened by elements like personable interactions, trust, emotional exchanges, and sincerity. These elements should always be considered and not disregarded during the development and implementation of AI applications. Understanding how to maintain these interpersonal relationships should also be incorporated within a provider's education and/or training.

Learning Environments for Parents and Children

Currently, AI encompasses many aspects of everyday life and natural complications can unknowingly arise if awareness and education is not pronounced. AI surrounds daily communication, entertainment, and social interactions. Along with these common notions, it is important for parents and children to comprehend how AI is being gradually incorporated in medicine. Parents as primary decision-makers must also increase their health literacy to provide optimal health care for their children and themselves. Maintaining balanced health management as a child may also guide them with future health decisions. For children, interactive AI workshops can also be held to increase their comprehension of how AI is transforming medicine and society.

Health Literacy

Health literacy refers to the ability to gather and comprehend health care information to make sufficient health decisions. It is generally determined by elements like age, cultural attitudes, education, religious beliefs, socioeconomic background, and related factors [52]. This ability is crucial to learn and improve as a parent to provide favorable health outcomes for their children. However, health literacy remains concerningly low among various countries. In the United States, a survey from 2003 revealed that approximately 14% of adults exhibit low health literacy, while 29% has basic literacy [53]. Moreover, low health literacy as a parent has been related to under par child health outcomes due to insufficient health comprehension [54, 55]. This literacy must be improved for the child's safety, especially in terms of emergencies. In the pediatric emergency room (ER), the natural environment may be busy and intense. Providers may not be able to properly communicate descriptive information regarding medications or treatments to the parent. Lack of understanding is therefore more likely to occur, especially those who are already at a disadvantage with low health literacy. To provide better learning environments for parents and children, systemic awareness and universal methods should be implemented to show the impact of low and high health literacy [52]. Providers should also contribute to this awareness by adaptively communicating information with parents of various health literacies.

The imperative need for enhancing health literacy is also primarily due to the increasing number of technological advances. As AI applications become pronounced within the healthcare system, parents must learn how to navigate and adapt to these changes. For example, health database systems like electronic health records (EHRs) can easily be accessed by the parent or patient. It provides both basic and intricate patient information and history. Parents should understand their children's health history to a certain extent to provide better health management. Many apps or web interfaces are also prevalent for conditions that require daily management. These can monitor pediatric heart disease, diabetes, or weight. Both parents and children should fully understand how to manage these apps or interfaces to maintain their health.

Artificial Intelligence Workshops

AI workshops are an enjoyable and unique way of incorporating AI awareness through education. These workshops can help children understand how AI is transforming diverse aspects of their health care. They can learn which applications are being implemented and present their own concerns towards these systems. It can also make them less wary of how these applications are being applied during future checkups and appointments. In a Patient and Public Involvement and Engagement workshop conducted by Visram et al., they presented several scenarios where AI was implemented and inquired how 21 adolescents and young adults felt about AI [56]. Some themes that were addressed were governance, human-centeredness, and trust. The participants expressed words towards AI and asked questions of how AI applications would affect the current and future healthcare system. There were 9 total scenarios which included AI-run nurses, chatbots, cleaning robots, talking robots, self-driving vehicles, sensor technology, virtual reality visits, and 3D printed hearts. The average score that the participants proposed for these scenarios was 5.3 on a 10-point Likert scale [56]. These results are valuable since they can help contribute to the research and development of future AI applications. This workshop should be utilized as a model for other learning environments since it incorporates education and allows children and young adults to offer their personal opinions towards AI.

Conclusion

Immense potential for AI in pediatric medicine is shown through past, current, and arising applications. The earliest applications such as voice recognition and da Vinci surgery system currently remain prevalent and provide favorable assistance to the provider and patient. Furthermore, these pioneering systems have inspired the development of AI programs amongst diverse areas. Numerous research and progress have been directed towards various subspecialties in pediatrics, such as oncology, cardiology, radiology, neurology, ophthalmology, and many more. Although most applications are not within a clinically implemented regimen, many show substantial promise for future execution. Prior to implementation, concerns relating to ethics and safety must be addressed to ensure the well-being of pediatric patients. The AI should follow an ethical framework and researchers, designers, and providers must be able to properly explain any implications to the parents, whom are the primary decision-makers. It is also imperative for academic and clinical health professionals to receive any education or training that will aid the success of AI in medicine. If the provider is unable to offer a substantial explanation, they can lose trust towards AI and can potentially endanger the safety of their patient. Unclear explanations would also risk confusing the parent and jeopardize the validity of proper informed consent. Education is also crucial for parents and children. Awareness should be spread for enhancing health literacy and addressing any of their concerns regarding AI applications. Overall, AI in pediatrics will expand significantly in coming years, but will require extensive and systemic guidance for future applications to prosper.

Conflict of Interest

The authors declare none financial or otherwise.

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