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# Artificial Intelligence in Revolutionizing Diagnosis, Treatment, and Preventive Care for Children's Oral Health: A comprehensive narrative review

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**KEYWORDS**

Artificial intelligence (AI), Pediatric dentistry, Machine learning (ML), Convolutional neural networks (CNNs), Diagnostics

**ABSTRACT:**

**Background:** Artificial intelligence (AI), introduced in 1956, has evolved into a valuable tool in healthcare. In pediatric dentistry, AI is increasingly applied to enhance diagnosis, treatment planning, preventive care, and behaviour management.

**Aim:** This review highlights current applications, benefits, limitations, and ethical considerations of AI in pediatric dentistry.

**Methods:** Recent literature was reviewed to explore AI uses in diagnostic imaging, caries detection, periodontal assessment, restorative and orthodontic care, forensic dentistry, and pediatric-specific innovations.

**Results:** AI supports clinicians in radiographic interpretation, pathology detection, and treatment planning through machine learning (ML), convolutional neural networks (CNNs), and generative models. In children, AI aids early childhood caries (ECC) risk prediction using genetic, salivary, and behavioral data; improves detection of mesiodens, supernumerary teeth, and ectopic eruptions; and facilitates tooth numbering and age estimation. CAD/CAM and augmented reality (AR) enhance restorative accuracy and orthodontic planning, while chatbots and gamification improve cooperation and reduce anxiety. Limitations include high costs, limited datasets, lack of standardization, and ethical issues related to privacy, liability, and bias. Frameworks such as MI-CLAIM, ACCEPT-AI, and PEARL-AI guide safe adoption.

**Conclusion:** AI is reshaping pediatric dentistry by augmenting clinical decision-making and patient care. Its future depends on robust validation, ethical safeguards, and child-centered design.

## 1. Introduction

The notion of artificial intelligence (AI) was first conceptualized in 1943; however, the term was formally introduced by John McCarthy at a scientific conference in 1956.(1) McCarthy characterized AI as a branch of science and engineering dedicated to enabling machines to comprehend what is conventionally regarded as intelligent behaviour and to construct systems capable of exhibiting such behaviour.(2) In essence, AI refers to technological approaches that allow machines to perform tasks or evaluate outcomes traditionally dependent on human cognition. Within the domain of healthcare, the advancement of AI has been associated with the development of computational programs designed to assist clinicians in diagnostic formulation, therapeutic decision-making, and prognostic prediction. Such systems are specifically intended to augment the role of healthcare providers in routine practice, particularly in tasks requiring complex data analysis and knowledge integration.(3)

## 2. Classification of AI

In dentistry, two principal branches of artificial intelligence (AI)—Convolutional Neural Networks (CNNs) and Machine Learning (ML)—are widely applied and highly promising.(4) CNNs, a deep learning method, excel at processing complex dental images, identifying anatomical structures and pathologies in radiographs and 3D scans, thereby improving diagnostic accuracy. ML, by analyzing patient datasets and clinical records, supports predictive modeling and treatment planning.(5)

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AI can also be classified as strong or weak. Strong AI aims for human-like intelligence and autonomous decision-making, while weak AI includes domain-specific tools such as ML and expert systems. Currently, deep learning, particularly CNNs and Generative Adversarial Networks (GANs), is a key research focus, enabling image recognition and data generation.(6)

Nguyen categorizes AI into four classes: statistical learning, neural networks, genetic algorithms, and hybrid systems.(7) Statistical learning applies probabilistic models for predictions, neural networks mimic brain architecture for pattern recognition, genetic algorithms use evolutionary principles for optimization, and hybrid systems integrate multiple strategies for complex problem-solving.(8)

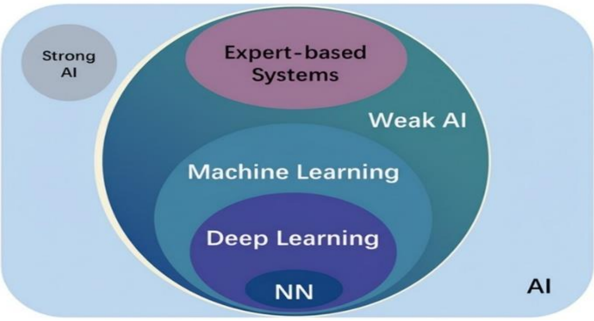


**Figure 1. Conceptual illustration showing the interrelationships among AI, strong AI, weak AI, expert systems, machine learning, deep learning, and neural networks (NN).** *Source: adapted from Ding H, Wu J, Zhao W, Matinlinna JP, Burrow MF, Tsoi JKH. Artificial intelligence in dentistry: A review. Front Dent Med. 2023;4:1085251. doi:10.3389/fdmed.2023.1085251.*

## 3. Application of AI in healthcare

Artificial intelligence (AI) enhances healthcare by training computational models to support diagnosis and reduce human error. Medical image interpretation has advanced from expert systems to atlas-based methods and now deep learning frameworks.(9) Large-scale radiographic datasets enable AI-driven analysis, while deep learning automates data mining to extract insights with minimal human input.(10) Wearable devices with AI can also aid early detection of critical conditions like strokes.

AI further supports rapid analysis of electronic health records and scientific databases, improving recognition of congenital anomalies. Among machine learning methods, support vector machines (SVMs) are widely used in medical research for classification and predictive modeling.(11)

## 4. Applications of AI in dentistry

The utilization of artificial intelligence (AI) within dentistry has expanded considerably, with applications spanning diagnostic imaging, oral pathology, radiology, caries detection, electronic record management, and robotic-assisted procedures. (8)

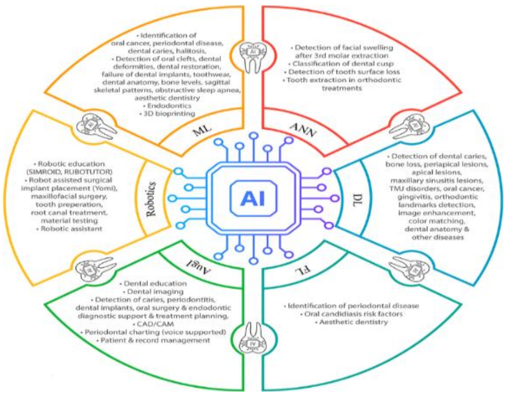


**Figure 2. Illustration of the main applications of AI in dentistry, including ANN, augmented intelligence, deep learning, fuzzy logic, and machine learning.** *Source: adapted from Rahim A, Khatoon R, Khan TA, Syed K, Khan I, Khalid T, Khalid B. Artificial intelligence-powered dentistry: Probing the potential, challenges, and ethicality of artificial intelligence in dentistry. Digit Health. 2024;10:20552076241291345. doi:10.1177/20552076241291345.*

One of the most prominent areas of advancement has been dental radiology, where AI-driven systems have demonstrated significant improvements in image interpretation.

In the case of two-dimensional (2D) radiographs, each image comprises thousands of pixels, providing a rich source of diagnostic information. By applying machine learning algorithms, specialized software platforms such as *Second Opinion* (Pearl), *Denti.AI*, and *VideaDetect* (VideaHealth) are able to process these images with enhanced precision, thereby assisting clinicians in identifying carious lesions and other pathologies more reliably (as illustrated in Figures 3 and 4).

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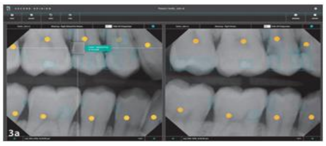

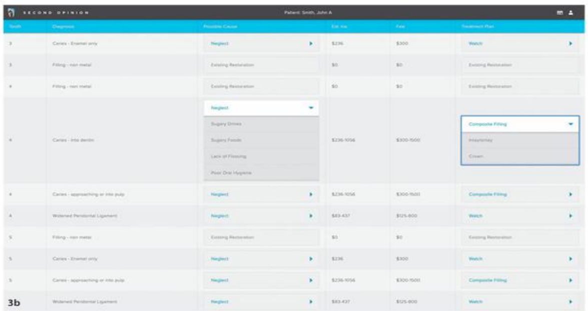

**Figures 3a and 3b. Application of AI in caries detection and treatment planning. (a) Interpretation of bitewing radiographs by AI software. (b) Automated generation of a treatment plan based on radiographic findings to support clinical decision-making.** ***Image courtesy of Pearl Inc.***

**Figure 4. AI-assisted detection of pathologic lesions. Bitewing radiographs are processed by trained AI algorithms, with suspected carious lesions highlighted (red boxes).** ***Image courtesy of VideaHealth.***

*Source: adapted from Chen YW, Stanley K, Att W. Artificial intelligence in dentistry: current applications and future perspectives. Quintessence Int. 2020;51(3):248–257. doi:10.3290/j.qi.a43952.*

Computer vision and deep learning platforms support clinicians by generating preliminary treatment proposals, which can be tailored to a practitioner's philosophy while leaving final decisions to the dentist. Currently, these systems are limited to relatively simple procedures such as fillings, partial coverage, and crowns.

AI has advanced from two-dimensional (2D) to three-dimensional (3D) applications. Orca-Dental AI, for example, offers software that can automatically segment the maxilla, mandible, and dentition, as well as recognize nerve pathways and detect pathology. Beyond radiography, 3D AI is also applied in intraoral scanning, where tools like Smart Margin and Scan Clarity Score (Pearl) enhance diagnostic accuracy and restorative planning.(12)

In periodontology, machine learning (ML) has been used to improve diagnosis and management of periodontitis. Convolutional Neural Networks (CNNs) applied to radiographs achieved diagnostic accuracies of about 81.0% for premolars and 76.7% for molars, highlighting clinical promise.(12,13)

AI also shows potential in orofacial pain and temporomandibular disorder (TMD) care, aiding in differential diagnosis and case classification.(14) Natural language processing (NLP) has been applied to electronic dental records (EDRs) to extract information such as smoking status, relevant to oral and systemic health.(15)

In forensic dentistry, AI is increasingly applied to age estimation from medical images, requiring collaboration between dental and forensic specialists to ensure reliability.(16)

## 5. Applications of AI in pediatric dentistry

Artificial intelligence (AI) is transforming healthcare, with growing impact in pediatric dentistry. Applications include diagnostic support, caries risk assessment, behavior management, treatment planning, and preventive care. By combining data-driven models with clinical expertise, AI enhances diagnostic accuracy, efficiency, and overall quality of care for children. The following sections highlight its main applications in pediatric dentistry.

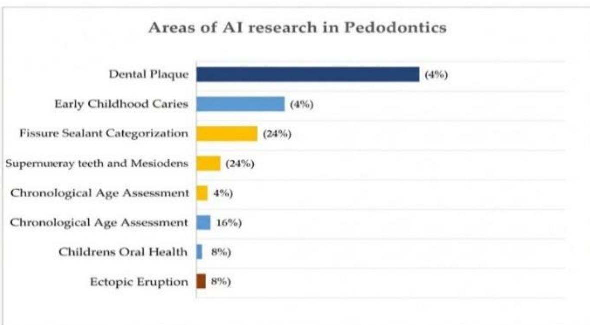


**Figure 5. Key areas of AI research in pediatric dentistry.**
*Source: adapted from Vishwanathaiah S, Fageeh HN,*

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*Khanagar SB, Maganur PC. Artificial intelligence: Its uses and application in pediatric dentistry—a review. Biomedicines.2023;11(3):788. doi:10.3390/biomedicines11030788.*

**Dental Plaque**

Dental plaque, a complex bacterial biofilm, often presents challenges in detection, even for experienced dental practitioners.(17) Traditional methods of plaque assessment are frequently regarded as either cumbersome or expensive,(18–20) although the introduction of digital imaging has contributed to improvements in plaque quantification and monitoring.(21,22) In an experimental study, You et al.(17) trained a Convolutional Neural Network (CNN) with 886 tooth images, demonstrating diagnostic performance comparable to that of a pediatric dentist. While factors such as image quality and interpretability remain limitations, these AI-based tools highlight the potential to assist not only clinicians but also parents in tracking and supporting children's oral hygiene practices.(4)

**Evaluating Dental Health in Children Using Algorithm-Designed Platforms**

In many low-resource and underdeveloped regions, oral health is frequently overlooked, with routine annual dental examinations remaining uncommon.(23) To address this gap, Wang et al.(23) and Liu et al.(24) designed machine learning–based oral health assessment toolkits within the PROMIS framework, aimed at predicting both the *Children's Oral Health Status Index (COHSI)* and the *Referral for Treatment Needs (RFTN)*. These models integrate dimensions of physical, psychological, and social well-being, thereby providing a more holistic evaluation of children's oral health. Such toolkits may serve as valuable resources for both parents and clinicians in monitoring oral health; however, their reliability is influenced by factors such as the survey design, parental awareness, and the robustness of the underlying algorithms.(23)

Further research has demonstrated that AI systems are capable of identifying complex response patterns that extend beyond conventional human interpretation,(25) underscoring their promise in areas such as clinical decision-making, health policy development, and educational initiatives. The advantages of these approaches include the delivery of rapid, accurate, and scalable results, offering significant potential for strengthening pediatric oral healthcare systems.(26,27)

**Recognition of Mesiodens and Supernumerary Dentition**

AI has demonstrated considerable potential in the diagnosis of mesiodens and supernumerary teeth through the application of CNN-based deep learning models.(28,29) Investigations by Ahn et al.(29) and Mine et al.(28) reported that models such as *SqueezeNet, ResNet, Inception-ResNet-V2, AlexNet, VGG16-TL,* and *InceptionV3-TL* were capable of detecting mesiodens in the mixed dentition with diagnostic accuracy comparable to expert evaluation, while offering greater speed and practical clinical applicability. Similarly, Kuwada et al.(30) identified *DetecNet* and *AlexNet* as useful for detecting impacted supernumerary teeth, although their performance was limited in cases involving unerupted permanent teeth. In contrast, Ha et al.(31) demonstrated that a *YOLOv3-based framework* could achieve effective detection across primary, mixed, and permanent dentitions.

Further contributions by Kaya et al.(32) and Kim et al.(33) emphasized the utility of deep learning in the identification of permanent tooth germs and the automation of mesiodens diagnosis. Nevertheless, challenges persist, particularly those related to small dataset sizes and difficulties in determining the number and precise location of anomalies. Collectively, evidence suggests that CNN-based deep learning models can provide valuable support to both general and pediatric dentists by enabling earlier detection, reducing chairside time, and facilitating treatment planning. However, widespread clinical implementation will require larger multicenter datasets and further model optimization.(28,30-33)

**Leveraging Artificial Intelligence for Prevention and Control of Early Childhood Caries**

Early Childhood Caries (ECC) is a multifactorial condition shaped by genetics, behavior, and environment.(34–37) Zaorska et al.(35) used artificial neural networks (ANNs) with SNP data to predict caries susceptibility, highlighting preventive potential. Machine learning (ML) models such as XGBoost, Random Forest, and LightGBM showed accuracy

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comparable to logistic regression, supporting their role in ECC risk screening and preventive planning.(38)

Biomarker-based approaches have also been explored: Koopaie et al.(39) improved ECC detection by combining salivary cystatin S with ML models, while Pang et al.(40) developed a Caries Risk Prediction Model (CRPM) integrating genetic and environmental factors. Karhade et al.(38) demonstrated that demographic and parental survey data alone could yield effective ECC classifiers.

During the COVID-19 pandemic, Ramos-Gomez et al.(41) used Random Forest to identify predictive parental survey items, enabling remote caries risk assessment. Overall, ML-driven ECC prediction frameworks show promise for early diagnosis, risk stratification, and preventive education, though integration into routine pediatric care remains limited and requires further validation.(42)

**AI-Powered Diagnostic Support for Fissure Sealant**

Dental sealants, routinely applied to molars as a preventive strategy against occlusal caries,(43) are visually distinctive, making them appropriate targets for AI-assisted detection. Within this domain, Convolutional Neural Networks (CNNs)—which require large annotated datasets for training—have been increasingly utilized in dentistry for image classification and restoration identification.(44) In this context, Schlickenrieder et al.(44) reported the successful development of a CNN model capable of detecting sealants from intraoral photographs, achieving diagnostic performance that surpassed conventional assessment methods. Despite these promising outcomes, challenges remain, including the necessity for repeated retraining, reliance on disease- or restoration-specific datasets, and the requirement for robust clinical validation before such systems can be adopted into routine dental practice.(4)

**Deep Learning Models for Chronological Age Estimation**

Accurate age estimation is a critical requirement in both clinical and forensic dentistry, particularly in contexts such as adoption, immigration, and treatment planning, where precise determination of a child's chronological age is essential.(45) Given that tooth development exhibits sexual dimorphism, with girls generally maturing earlier than boys, conventional clinical approaches often provide limited accuracy. By contrast, pantomographic assessments based on tooth bud mineralization have been shown to offer more reliable outcomes.(45)

In this regard, Zaborowicz et al.(45) introduced a neural modeling approach employing digital pantomographic images from children aged 4–15 years, reporting near-perfect accuracy, albeit restricted to pantomographic datasets. Building on this work, Zaborowicz, M. et al.(45) evaluated three deep neural network models, confirming that neural algorithms can effectively estimate chronological age by integrating both dental and skeletal indicators. Similarly, Bunyarit et al.(46) applied artificial neural networks (ANNs) to Demirjian's dental maturity scores, successfully estimating age in Malaysian Chinese children. Lee et al.(47) further advanced the field by developing ML algorithms utilizing 18 radiomorphometric parameters, which outperformed traditional techniques in terms of precision and reliability.

Taken together, these studies underscore the superiority of ANN- and ML-based systems in delivering age assessments that are faster, more accurate, and reproducible compared with conventional methods. Nonetheless, broader validation across diverse populations, along with the incorporation of multimodal datasets, will be essential before such AI-driven tools can be integrated into routine pediatric and forensic dental practice.(4)

**AI-Based Tooth Detection Using Neural Networks**

Convolutional Neural Networks (CNNs) have become increasingly prominent in pediatric dentistry, particularly in applications related to tooth recognition and numbering, thereby forming the foundation of automated diagnostic systems.(48,49) Compared with traditional region-based or thresholding techniques, CNN-based models demonstrate markedly superior performance in tooth segmentation and mapping.(47,48) For instance, Caliskan et al.(50) successfully utilized CNN algorithms to identify submerged molars, while Kilic et al.(48) employed a *Faster R-CNN Inception v2* model to detect and number primary teeth on panoramic radiographs, achieving high sensitivity and emphasizing the potential forensic relevance of such systems. Similarly, Kaya et al.(32) applied *YOLOv4*, a one-stage detector, to

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recognize and enumerate both primary and permanent teeth with notable speed and precision, underscoring its suitability for real-time clinical use.(32)

Comparative analyses indicate that two-stage detectors such as *R-CNN, Faster R-CNN,* and *Mask R-CNN* provide slightly higher accuracy but at the expense of slower processing speeds and greater computational requirements.(49) Conversely, YOLO models, as single-stage detectors, offer a balanced approach by enabling rapid, real-time detection with minimal compromise in accuracy.(32) Collectively, these advancements in CNN-based tooth recognition highlight significant contributions to digital dentistry, improving diagnostic efficiency, accuracy, and potential applications in both clinical care and forensic identification.(4)

**AI-Assisted Diagnosis of Ectopic Eruption in First Permanent Molars**

Ectopic eruption, most commonly involving the maxillary first molar during the early mixed dentition stage, can result in complications such as arch constriction, space deficiency, malocclusion, and resorption of adjacent teeth.(51,52) Timely diagnosis is therefore critical and has traditionally relied on clinical evaluation in combination with radiographic techniques including CBCT, panoramic, occlusal, and periapical imaging. However, panoramic radiographs are limited by two-dimensional distortion and image superimposition, which may compromise diagnostic accuracy.(53) Recent advances in radiomics and AI have introduced multi-layered CNN architectures that enhance both precision and reproducibility in detecting ectopic eruptions. For example, Zhu et al.(53) compared several segmentation models—U-Net, R2U-Net, attention U-Net, and nnU-Net—and demonstrated that nnU-Net achieved superior performance in semantic segmentation by dynamically adapting to dataset characteristics, thereby producing optimal outcomes.(51,54–56) In a related study, Liu et al.(57) developed an automated screening system that identified ectopic molars with accuracy levels comparable to those of experienced pediatric dentists.

Although these findings highlight the ability of AI-enhanced image recognition to significantly improve diagnostic reliability, current deep learning models remain insufficient as standalone diagnostic tools. Nonetheless, AI-assisted methods represent a promising adjunct to clinical expertise, offering earlier and more consistent detection of ectopic eruptions.(4)

| AI Technique/Algorithm Architecture | Diagnostic Tasks | Functionality of the AI Model | Input Features |
|---|---|---|---|
| Machine Learning (ML) | Automated estimation of the age | Landmarks | Radiomorphometric data [Lee, Y.H. et al.] [38] |
| Artificial Neural Networks (ANNs) | For predicting children's oral health status index (COHSI) and referral for treatment needs (RFTN) | Oral health status | Data sets [Wang, Y. et al.] [28] |
| | Classification of early childhood caries | Dental caries | Data sets [Karhade, D.S. et al.] [29] |
| | Determining the chronological age | Age assessment | Digital pantomographic images [Zaborowicz, K. et al.] [32] |
| | Caries risk prediction | Dental caries | Data sets [Pang, L. et al.] [26] [Ramos-Gomez, F. et al.] [30] |
| | Predicting early childhood caries | Dental caries | Data sets [Park, Y.H. et al.] [25] [Koopaie, M. et al.] [27] |
| | Impact of oral health on adolescents' quality of life | Adolescent quality of life | Data sets [Gajic, M. et al.] [7] |
| | Age estimation | Dental age and Chronological age | Panoramic images [Banyarit, S.S. et al.] [33] |
| **AI Technique/Algorithm Architecture** | **Diagnostic Tasks** | **Functionality of the AI Model** | **Input Features** |
| Deep Learning (CNNs) | Detecting plaque on primary teeth | Dental Plaque | Intra oral photographs [You, W. et al.] [23] |
| | Detecting and categorizing fissure sealants | Fissure sealants | Digital photographs [Schlickenrieder, A. et al.] [31] |
| | Predicting dental caries based on chosen polymorphisms | Dental caries | Data sets [Zaorska, K. et al.] [24] |
| | Detection and enumeration of the deciduous teeth | Tooth | Panoramic images [Kılıc, M.C. et al.] [34] |
| | Automatically classify mesiodens in primary or mixed dentition | Mesiodens | Panoramic radiographs [Ahn, Y. et al.] [21] |
| | Identification of mesiodens in growing children/various dentition groups | Mesiodens | Panoramic radiographs [Kim, J. et al.] [41] [Ha, E.G. et al.] [24] |
| | Detecting the presence of supernumerary teeth during the early mixed dentition stage | Supernumerary teeth | Panoramic radiographs [Mine, Y. et al.] [3] |
| | Classifying maxillary impacted supernumerary teeth | Supernumerary teeth | Panoramic radiographs [Kuwada, C. et al.] [22] |
| | Estimating the age | Dental age | Digital Pantomographs [Zaborowicz, M. et al.] [37] |
| | Automated tooth detection and numbering | Tooth detection | Panoramic images [Kaya E et al.] [10] [Kaya E et al.] [39] |
| | Detection and classification of submerged teeth | Tooth detection [Submerged teeth] | Panoramic radiographs [Caliskan S et al.] [35] |
| | Detection of ectopic eruption of permanent maxillary molar | Ectopic eruption | Panoramic radiographs [Zhu H et al.] [36] [Liu J] [40] |

**Table 1. Overview of AI models developed for various diagnostic applications in dentistry.**
Source: adapted from Vishwanathaiah S, Fageeh HN, Khanagar SB, Maganur PC. Artificial intelligence: Its uses and application in pediatric dentistry—a review. Biomedicines. 2023;11(3):788. doi:10.3390/biomedicines11030788.

**AI-Powered Solutions in Pediatric Restorative Dentistry**

A key advantage of incorporating AI-enabled CAD/CAM systems into pediatric restorative dentistry is the substantial reduction in chairside time. Since young patients often have limited tolerance for prolonged procedures, the ability to complete treatments more quickly is particularly beneficial. By streamlining the design and fabrication workflow, AI-assisted CAD/CAM technologies facilitate faster, more efficient restorative care.(58)

Moreover, these systems enable the production of customized restorations tailored to the unique morphology of each child's dentition. This personalization not only improves the quality and longevity of the restorations but also enhances patient comfort and reduces the likelihood of multiple appointments, thereby optimizing both clinical efficiency and treatment outcomes.(5)

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**AI-Assisted Approaches in Pediatric Endodontics and Orthodontics**

Augmented Reality (AR) is emerging as a valuable innovation in dentistry, providing enhanced visualization and patient engagement by integrating diagnostic information from radiographs, CT scans, and MRI imaging into real-time clinical applications.(45) Within the scope of diagnostic AI, Altındag et al. demonstrated that the *Mask R-CNN* model could reliably and sensitively detect pulp stones on dental radiographs, underscoring the potential of AI systems in routine dental screening.(59)

Significant progress has also been observed in orthodontics, where AI has enabled the design of personalized appliances for children, improving both esthetics and compliance.(17) In parallel, AR technologies complement these advances by allowing orthodontists to simulate treatment outcomes, facilitate more effective communication with patients and parents, and even support remote monitoring through AR-powered applications, thereby reducing the need for frequent in-office visits.(60)

Taken together, the integration of AI and AR enhances diagnostic accuracy, strengthens patient–clinician communication, and improves overall treatment efficiency in both pediatric and orthodontic practice.(5)

**AI for Precision in Local Anesthesia**

AI has demonstrated significant potential in enhancing the precision and safety of local anesthesia administration in pediatric dentistry. By improving the resolution and interpretability of sonographic images, AI-based algorithms enable clearer visualization of anatomical landmarks, thereby assisting clinicians in identifying target sites with greater accuracy.(61,62) This improved precision not only minimizes the likelihood of procedural complications but also ensures more effective anesthetic delivery.

In addition, AI-assisted anesthesia contributes to a more positive patient experience by reducing discomfort, facilitating quicker recovery, and fostering trust in treatment outcomes. Such innovations support dental practitioners in achieving higher levels of accuracy while simultaneously improving cooperation and acceptance of dental procedures among children and their parents.(5)

**AI-Assisted Child Behaviour Guidance**

AI offers considerable promise in the domain of behaviour management for pediatric dental patients by enabling individualized support and engagement strategies. Through personalized learning approaches, AI systems can adapt to each child's cognitive style and developmental needs, which is particularly beneficial for children with learning disabilities. The incorporation of gamification elements—such as reward systems, points, and progression levels—further enhances motivation and transforms the dental experience into a more positive and enjoyable one. Moreover, the use of AI-driven chatbots, equipped with natural language processing (NLP) capabilities, provides real-time emotional support by identifying signs of stress or anxiety in young patients and offering appropriate coping mechanisms. Collectively, these innovations contribute to creating a calmer, more reassuring clinical environment and foster greater cooperation from children during dental treatment.(63)

## 6. Future perspectives of AI in pediatric dental care

AI is anticipated to play a transformative role in dentistry by enabling greater precision, facilitating rapid information exchange, and generating deeper insights into the etiology and management of multifactorial oral diseases.(12) In the future, dental practices may incorporate an AI-integrated Comprehensive Care System that synthesizes patient histories, radiographs, and three-dimensional imaging to assist in diagnosis, treatment planning, error minimization, and prognosis prediction, while maintaining the clinician's central decision-making role. Applications are also expected to expand into prosthodontics through AI-driven CAD/CAM workflows, implant dentistry using CBCT and intraoral scan data for optimized planning, and the automated design of prosthetic restorations.(12)

Dental institutions and private clinics may further benefit by developing AI-powered patient data repositories, continuously updated from scientific databases, while employing intraoral scanning to ensure more objective clinical evaluations. The aggregation of large-scale

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radiographic and scan-based datasets could strengthen clinical training, improve ergonomic practices, and support evidence-based decision-making at the business and organizational level. Nevertheless, effective implementation will require clinicians to have a fundamental understanding of AI models and awareness of their limitations.(12)

Broader opportunities include the use of AI-enabled teledentistry for remote consultations, administrative automation in tasks such as scheduling and billing, and the integration of robot-assisted dental procedures to enhance precision.(64) AI is also poised to impact dental insurance systems through faster claim processing and real-time approval mechanisms. Beyond clinical efficiency, AI can contribute to improving the patient experience by tailoring visit schedules, modifying environmental factors, and adjusting comfort settings to individual preferences—ultimately fostering improvements in both oral and systemic health.(12)

## 7. Limitations and concerns of AI

Despite its promise, the integration of artificial intelligence (AI) in dentistry presents several important challenges and risks. AI algorithms may identify associations that are correlational rather than causal, which can lead to potential misinterpretation if applied inappropriately. To mitigate such risks, close collaboration between clinicians and engineers is critical, while issues of professional liability and adherence to privacy frameworks, such as HIPAA, remain key concerns.(12)

The use of generative AI technologies, including chatbots that rely on natural language processing to simulate dialogue, further highlights ethical and regulatory challenges. Because these systems are trained on uncurated internet data, they may produce inconsistent or misleading outputs, underscoring the need for rigorous oversight. Nonetheless, when implemented responsibly under the guiding principle of "first, do no harm," AI retains substantial potential to advance safer, more accessible, and equitable healthcare delivery.(64)

Another major limitation is the absence of standardized reporting protocols in dental AI research, which has prompted the creation of the MI-CLAIM checklist to strengthen transparency, reproducibility, and methodological rigor. Additionally, the high initial investment required for hardware, software, and training continues to represent a significant barrier, particularly for smaller pediatric dental practices.(5)

## 8. Ethical considerations in AI for child health

The ethical application of AI in pediatric dentistry must be grounded in the four core bioethical principles: autonomy, non-maleficence, beneficence, and justice. This requires the generation of robust evidence and the development of child-centered AI systems, ideally validated through randomized controlled trials (RCTs) to ensure safety and reliability.(65) To further address potential age-related biases, the ACCEPT-AI framework has been introduced as a structured approach for evaluating pediatric AI research. This framework incorporates pre-processing, in-processing, and post-processing strategies, thereby enhancing transparency andequity across the entire AI life cycle.(66)

| S. no | Regulation | Description |
|---|---|---|
| 1 | Transparency and documentation | Complete information about the AI product to ensure trust among developers, manufacturers, and end-users. |
| 2 | Risk management | All risks associated with AI health systems and devices, be extensively discussed. |
| 3 | Intended usage and data validation | It must be made clear to promote regulation and ensure safety. |
| 4 | Data standardization | Thoroughly test AI systems before release to make sure biases and faults are not amplified. |
| 5 | Confidentiality and data security | Accentuation on comprehending the boundaries of jurisdiction and the need for consent. |
| 6 | Collaboration | Promoting cooperation among government agencies, industry representatives, developers, patients, healthcare providers, and regulatory authorities may enhance the security and quality of an AI system. |

AI: artificial intelligence; WC-RC: working group on regulatory considerations.

**Table 2.** WHO Working Group on Regulatory Considerations (WC-RC) in relation to artificial intelligence. Abbreviations: AI = artificial intelligence; WC-RC = Working Group on Regulatory Considerations.

Protecting children in the context of AI-enabled applications requires robust safeguards, including restrictions on harmful content, access to parental safety tools, and limitations on unsafe interactions or location-sharing features.(65) Addressing the digital divide will further necessitate coordinated efforts by governments and industry stakeholders to invest in technological infrastructure, adopt child-centered AI policies, and support high-quality pediatric AI research.(66)

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To guide the ethical development and deployment of these technologies, the PEARL-AI (Pediatrics EthicAl Recommendations List for AI) framework offers practical, continuously updated recommendations for clinicians, researchers, and developers. This framework ensures that pediatric AI solutions uphold ethical principles while accounting for the distinct vulnerabilities and needs of children.(65)

## 9. Conclusion

Although artificial intelligence (AI) may function as the "brain" of modern innovation, in pediatric dentistry the "heart" will always be the dentist. No longer a futuristic concept, AI has become a transformative force that is steadily reshaping the field. Its applications—from caries risk prediction and behavioral assessment to radiographic interpretation, personalized treatment planning, and preventive strategies—are redefining the way oral healthcare for children is conceived and delivered. By enhancing precision, improving efficiency, and expanding access across diverse clinical settings, AI empowers pediatric dentists to provide care with greater impact and consistency.

Yet, with this promise comes profound responsibility. Ethical safeguards, data privacy, affordability, and rigorous clinical validation must be prioritized to ensure that technology truly serves the best interests of children. Crucially, AI should not be viewed as a substitute for professional expertise but as a powerful adjunct—a tool that amplifies the pediatric dentist's knowledge, judgment, and compassion while preserving the uniquely human elements of empathy and artistry.

The future of pediatric dentistry lies in a harmonious partnership between innovation and compassion—where advanced algorithms complement, but never replace, the healing presence of a caring dentist. By embracing AI with thoughtful intention, the profession can aspire toward a future that is not only technologically sophisticated but also profoundly child-centered. Ultimately, the evolution of pediatric dentistry is not defined by *man versus machine*, but by *man with machine—for the child*.

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