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Review

Current Evidence of Artificial Intelligence Tools Applied in Pediatric Dentistry: A Narrative Review

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Abstract

Background. Artificial intelligence (AI) is increasingly recognized as a transformative technology in healthcare, with growing interest in its applications within pediatric dentistry. Given the unique clinical, developmental, and behavioral characteristics of pediatric patients, AI-based systems may offer valuable support in improving diagnosis, prevention, and treatment planning. **Methods.** A narrative review was conducted to synthesize current evidence on AI applications in pediatric dentistry. A comprehensive search strategy, including predefined keywords and free terms, was applied across multiple databases (Embase, Scopus, PubMed, and Web of Science) up to 1 January 2026. Reviews addressing AI-based technologies in pediatric dental care were selected and analyzed. **Results.** The available literature indicates that AI is being progressively applied across multiple domains of pediatric dentistry, although with varying levels of evidence. More extensively investigated areas include diagnostic imaging, caries detection, orthodontic assessment, and growth evaluation, where AI systems—particularly those based on machine learning and deep learning—have demonstrated high accuracy and reproducibility. Other emerging fields, such as remote monitoring, behavioral management, preventive strategies, and patient education, show promising potential but remain less explored. Overall, AI-based tools appear to enhance diagnostic support, enable early detection of oral conditions, and contribute to more personalized and efficient clinical workflows. **Conclusions.** AI represents a rapidly evolving adjunct in pediatric dentistry with the potential to improve clinical decision-making, preventive care, and patient management. Despite encouraging results, further validation in real-world settings, along with careful consideration of ethical, legal, and data-related challenges, is required to support its responsible integration into routine clinical practice.

Keywords: artificial intelligence; pediatric dentistry; pedodontics; deep learning; computerized diagnosis

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1. Introduction

Artificial Intelligence (AI) is typically described as a computer program that can perform cognitive tasks [1,2]. It has increasingly been embraced in healthcare sectors, including dentistry. Within the last five years, there has been a remarkable surge in AI-focused research specifically addressing dental applications [3]. This burgeoning interest is driven by the assumption that AI presents unique opportunities in enhancing diagnostic accuracy, improving treatment planning, and optimizing patient management. These opportunities also concern the pediatric population, whose clinical needs and behaviors differ considerably from those of adults [4]. Pediatric dentistry involves not only the management of common dental diseases like caries but also the consideration of growth and development, behavioral management, and preventive strategies suited to children and adolescents [5]. The traditional clinical approach—while effective—often relies heavily on subjective clinical expertise and time-intensive procedures that may be challenging in a pediatric setting due to cooperation issues and developmental variability. Against this backdrop, AI technologies, particularly machine learning (ML) and deep learning (DL), offer the potential to revolutionize pediatric dental care by automating complex tasks, extracting meaningful patterns from large datasets, and supporting evidence-based personalized interventions [6–8]. Furthermore, over the last five years, there has been an "explosion" of publications on diverse AI applications in pediatric dental care, ranging from automated radiographic diagnostics and caries risk prediction to orthodontic growth assessment and behavioral analytics. The present narrative review aims to synthesize the current evidence on this technology by critically exploring and integrating recent advances in AI within pediatric dentistry, with a focus on practical implications and applications. The study provides a thematic synthesis of the latest developments, emphasizing conceptual connections, strengths, limitations, and future directions, thereby offering the scientific community a cohesive understanding of how AI is reshaping pediatric dental practice.

2. Materials and Methods

This paper presents a narrative review designed to synthesize the current landscape of Artificial Intelligence (AI) in pediatric dentistry (Table A1). This approach was chosen to integrate the multi-faceted evidence available in the field, merging clinical, diagnostic, and ethical perspectives that are often addressed separately in other publications. The search strategy included the terms Artificial Intelligence, AI, automated diagnostics, computer-assisted diagnosis, supervised learning, unsupervised learning, convolutional neural networks, deep learning, machine learning, pedodontics, pediatric dentistry, growing children, and review combined with Boolean operators in order to ensure the inclusion of appropriate papers, i.e., studies addressing the applications of AI in pediatric dentistry. The literature search was conducted up to January 2026. The search strategy was adjusted for EMBASE, Web of Science, PubMed, and Scopus databases and was conducted without restrictions on language or publication status. All titles and abstracts were first assessed, and only published reviews (regardless of review type, i.e., systematic review, meta-analysis, scoping review, narrative review) that profiled and discussed the applications and implications of AI in pediatric dentistry were included. The synthesis focused on identifying key technological trends and clinical implications. By evaluating and integrating findings from various reviews, this manuscript aims to provide a unified overview that captures nuances often missed by narrower systematic protocols. The collected evidence was qualitatively analyzed to discuss the practical integration of AI in the management of pediatric patients.

3. Results

Nine articles were deemed suitable for inclusion in the current review and narrative elaboration (Table 1). The qualitative synthesis of the included reviews highlights a multi-faceted integration of Artificial Intelligence (AI) within pediatric dentistry, categorized into different domains. Such domains comprise all the actual practical implications and applications of AI in the clinical management of pediatric patients in dentistry. Each domain was paired with an AI-generated image that figuratively illustrates the relative content (Figures 1–6). Figure 1 shows the general roadmap related to the actual applications of AI in pedodontics, according to the information collected in the data extraction form.

Table 1. Articles included in the present review.

Authors	Years	Journal	Title
Acharya S. et al. [9]	2024	Journal of Clinical Pediatric Dentistry	Role of artificial intelligence in behavior management of pediatric dental patients—a mini review.
Alessa N. et al. [10]	2024	Journal of Pharmacy and Bioallied Sciences	Application of Artificial Intelligence in Pediatric Dentistry: A Literature Review.
Alharbi N et al. [11]	2024	Cureus	AI-Driven Innovations in Pediatric Dentistry: Enhancing Care and Improving Outcome.
La Rosa S. et al. [4]	2024	Healthcare MDPI	The Implications of Artificial Intelligence in Pedodontics: A Scoping Review of Evidence-Based Literature
Naeimi S.M. et al. [12]	2024	Bioengineering MDPI	Artificial Intelligence in Adult and Pediatric Dentistry: A Narrative Review
Rokhshad R. et al. [13]	2024	Pediatric Dentistry (American Academy Pediatric Dentistry)	Current Applications of Artificial Intelligence for Pediatric Dentistry: A Systematic Review and Meta-Analysis
Rokhshad R. et al. [14]	2024	Pediatric Dentistry (American Academy Pediatric Dentistry)	Artificial Intelligence in Early Childhood Caries Detection and Prediction: A Systematic Review and Meta-Analysis
Tanna D.A. et al. [15]	2024	International Journal of Clinical Pediatric Dentistry	Tech Bytes-Harnessing Artificial Intelligence for Pediatric Oral Health: A Scoping Review.
Vishwanathaiah S. et al. [16]	2023	Biomedicine MDPI	Artificial Intelligence: Its Uses and Application in Pediatric Dentistry: A Review

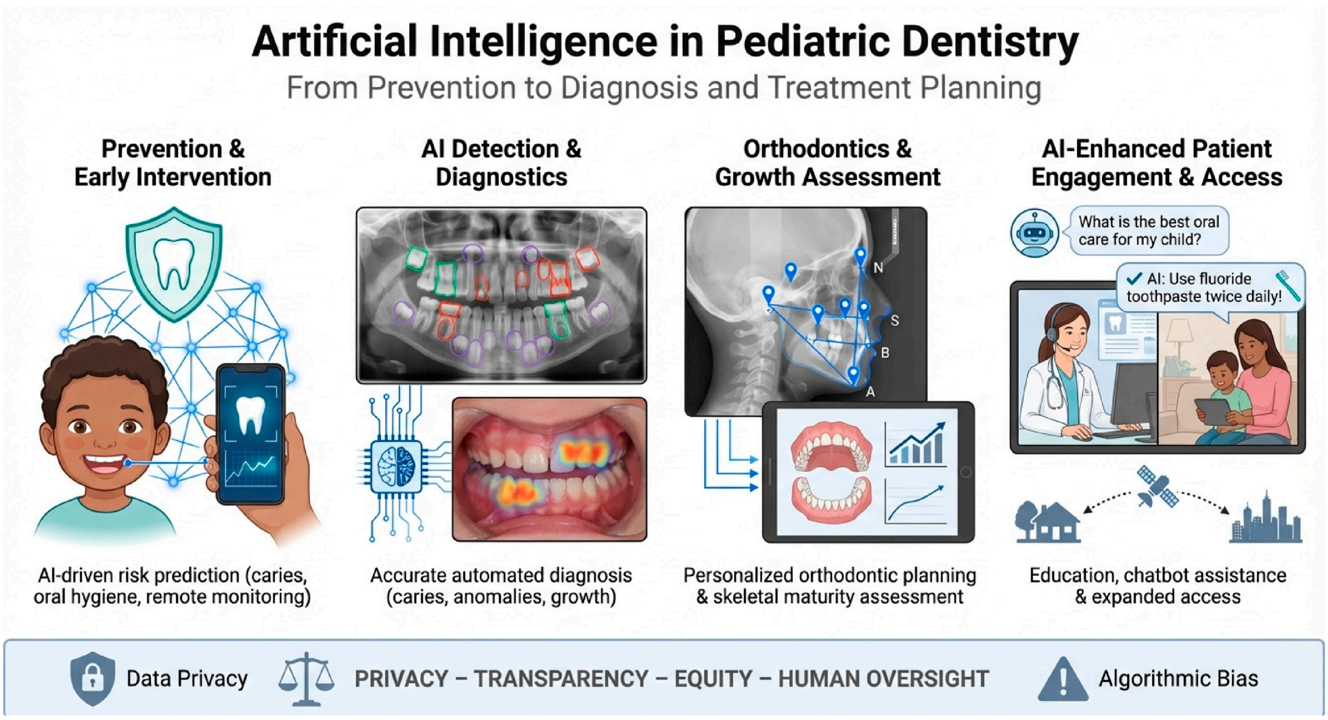

Figure 1. Roadmap of the actual fields of application of AI-based technology in pediatric dentistry.

4. Discussion

The analysis of the available literature suggests that artificial intelligence (AI) is progressively gaining relevance within the field of pediatric dentistry, with an increasing number of studies exploring its potential clinical applications. Although the degree of development and scientific validation varies across different areas, it is evident that AI is beginning to be investigated in multiple aspects of pediatric dental care. This growing body of research reflects the broader interest in integrating advanced technologies into clinical practice and highlights the potential role that AI may assume in the near future in the management of pediatric patients. In this context, the following sections aim to provide a structured discussion of the current evidence, outlining the main areas in which AI has been applied and examining their clinical implications.

4.1. Caries Management and Oral Hygiene

Early childhood caries (ECC) represents a multifactorial disease influenced by a complex interplay of behavioral, environmental, and biological determinants in pediatric populations [17]. While traditional models have primarily emphasized behavioral and environmental contributors, increasing evidence highlights the relevance of genetic susceptibility, with several genes and single-nucleotide polymorphisms (SNPs) associated with ECC [18,19]. However, these biological variables have not always been consistently incorporated into predictive frameworks, thereby limiting the accuracy of conventional risk assessment models [19]. In this context, artificial intelligence (AI) has emerged as a powerful tool to integrate multidimensional datasets and improve both prediction and management of ECC. Machine learning (ML) algorithms—including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and ensemble methods such as XGBoost and Random Forest—have been successfully applied to analyze a wide spectrum of predictors. These include salivary biomarkers (e.g., cystatin S), birth weight, age, parental perception of oral health, and genetic polymorphisms [20–22]. The integration of such heterogeneous variables enables a more refined and individualized risk stratification, thereby supporting preventive strategies tailored to the specific profile of each patient.

Importantly, recent studies have demonstrated that AI-based predictive models outperform traditional statistical approaches, such as logistic regression, particularly in capturing nonlinear interactions among risk factors [23]. Deep learning architectures trained on large-scale datasets incorporating behavioral, microbiological, and socioeconomic variables have consistently shown superior predictive performance, with area under the curve (AUC) values frequently exceeding 0.85 in ECC prediction tasks [24,25]. These findings support a paradigm shift toward precision prevention, where interventions are dynamically adapted to individual risk profiles rather than applied uniformly across populations.

Beyond risk prediction, AI has also shown considerable potential in improving diagnostic accuracy in oral hygiene assessment. CNN-based models have demonstrated the ability to detect dental plaque from intraoral photographs acquired with low-cost digital devices, achieving performance comparable to expert pediatric dentists [22]. This capability not only enhances diagnostic standardization but also lays the groundwork for remote monitoring strategies, which will be further discussed in the following section. Moreover, AI-driven systems have proven effective in detecting caries lesions and molar-incisor hypomineralization (MIH) from photographic images, reducing the subjectivity inherent in clinical examination [26]. Similarly, deep learning algorithms have been applied to assess the presence and integrity of pit-and-fissure sealants, providing an objective evaluation of preventive treatment outcomes [27]. The integration of AI into digital imaging devices further extends these capabilities, allowing real-time identification of early carious lesions with promising accuracy [27].

In addition, emerging multimodal approaches combining AI with quantitative light-induced fluorescence (QLF) and near-infrared transillumination technologies have demonstrated enhanced sensitivity in detecting early demineralization [28]. These systems are

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particularly relevant in the context of minimally invasive dentistry, as they enable the identification of non-cavitated lesions that may otherwise remain undetected during routine examinations. Taken together, these advancements underscore how AI is progressively shifting pediatric dentistry from a reactive, treatment-oriented model toward a proactive, prevention-centered approach, ultimately reducing disease burden and improving long-term oral health outcomes.

4.2. AI-Driven Remote Monitoring in Pediatric Dentistry

Building upon the diagnostic capabilities described above, recent technological advances have enabled the extension of AI applications beyond the clinical setting, giving rise to AI-driven remote monitoring (AIRM) systems. These approaches leverage smartphone technology and artificial intelligence (AI) to allow caregivers or older children to capture intraoral images at home, which can then be analyzed either automatically or by clinicians through digital platforms [29]. This evolution represents a natural progression from image-based diagnostics to continuous, decentralized patient monitoring. AIRM facilitates the early detection of caries, plaque accumulation, enamel demineralization, gingival inflammation, and eruption anomalies, thereby supporting preventive care while reducing the need for frequent in-office visits [29]. Such an approach is particularly advantageous in pediatric populations, where compliance, accessibility, and behavioral factors often represent significant challenges.

Evidence indicates that teledentistry-based approaches can achieve diagnostic accuracy comparable to conventional clinical examinations. For instance, caregiver-acquired intraoral photographs have demonstrated sensitivity and specificity similar to in-person assessments in detecting caries in school-aged children [30]. Likewise, smartphone-assisted maternal screening for ECC has shown strong concordance with professional evaluations, highlighting the feasibility of home-based monitoring strategies [31]. Recent developments have further enhanced these systems through the integration of AI-powered platforms capable of automated image analysis and asynchronous clinician review [32]. Although initially developed within orthodontics, these technologies are increasingly being adapted to broader pediatric dental applications, including plaque monitoring and eruption tracking.

The clinical implications of AIRM are substantial. These systems improve access to care, particularly in underserved or geographically remote areas [33], while simultaneously reducing the burden of in-office visits and associated stress for pediatric patients [30]. Furthermore, they enable earlier intervention by facilitating timely detection of pathological changes [30], and they enhance parental engagement by promoting active participation in the child's oral health management [33]. In addition, AI-assisted teledentistry programs have shown potential to reduce healthcare disparities by improving early detection rates in underserved pediatric populations [34]. Nevertheless, certain limitations must be acknowledged. The reliability of AIRM depends heavily on the quality of image acquisition, which may be influenced by factors such as lighting, angulation, and caregiver compliance [35]. Additionally, these systems cannot replace comprehensive in-person examinations requiring radiographic imaging, tactile assessment, or operative procedures; therefore, they should be considered complementary tools primarily suited for screening, monitoring, and triage [29]. Overall, AI-driven remote monitoring represents a significant step toward more accessible, preventive, and patient-centered pediatric dental care.

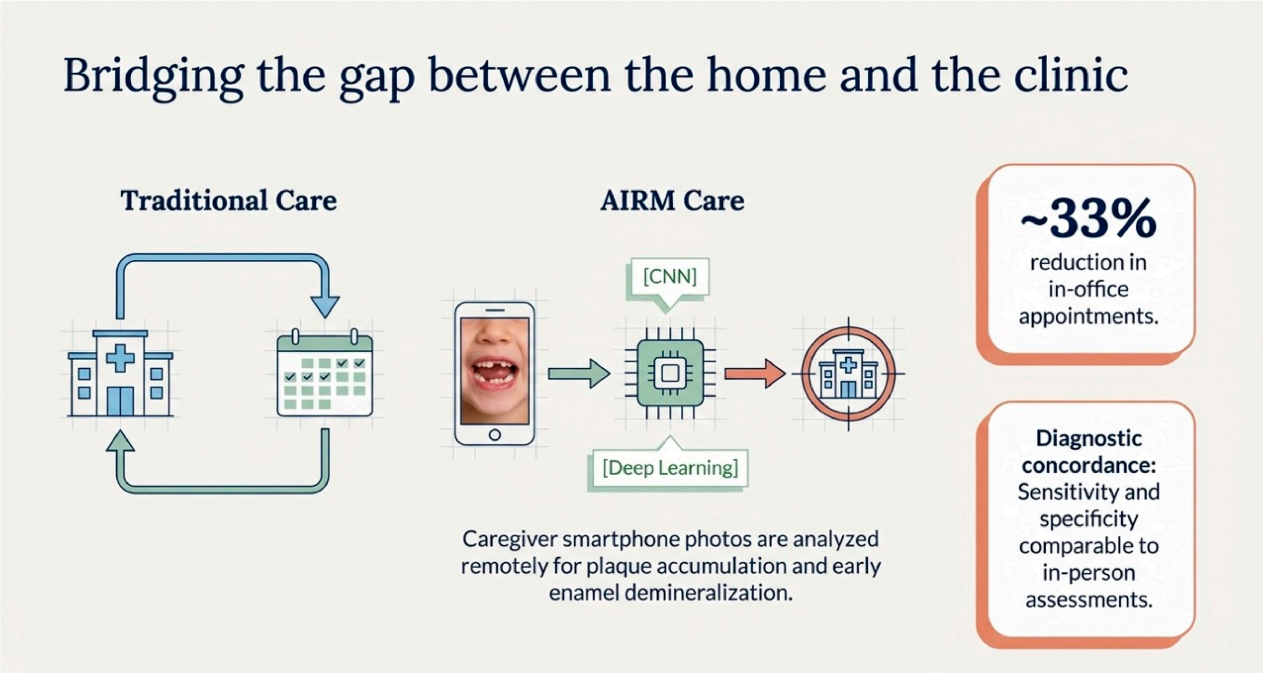

Figure 2. AI-driven remote monitoring in pediatric dentistry.

4.3. Diagnosis and Identification of Dental Anomalies

In parallel with its role in preventive and remote care, AI has significantly enhanced radiographic diagnostics, which remain a cornerstone of pediatric dental evaluation. The application of deep learning (DL) models to imaging data has improved the detection of dental anomalies, particularly in complex developmental stages such as mixed dentition. Architectures including ResNet, YOLOv3, VGG16, and Inception-ResNet-V2 have demonstrated high diagnostic accuracy—often exceeding 90%—in identifying mesiodens and supernumerary teeth on panoramic radiographs [36]. These tools are especially valuable in clinical scenarios where anatomical complexity or limited clinician experience may hinder accurate diagnosis, such as during transitional dentition phases [37]. Furthermore, automated tooth detection and numbering systems based on frameworks such as Faster R-CNN and YOLOv4 facilitate early identification of agenesis, delayed eruption, and other developmental anomalies, supporting timely clinical intervention [38]. Similarly, models such as nnU-Net and YOLOv3 have shown high precision in detecting eruption-related conditions, including submerged molars and ectopic eruptions, in some cases surpassing human expert performance [39]. AI applications also extend to the identification of less common anomalies, such as taurodontism, through U-Net-based architectures [40], as well as the detection of craniofacial conditions like cleft lip and palate from radiographic images [36]. Additionally, the automated recognition of permanent tooth germs supports early diagnosis and improved treatment planning [41].

Despite these promising outcomes, limitations persist. Model performance may be affected by incomplete tooth eruption, overlapping anatomical structures, and limited dataset diversity [42]. Fully automated systems, including those based on DeeplabV3+ or Pytorch-based U-Net, still encounter challenges in accurately determining the number and spatial distribution of anomalies [43]. Comparative studies evaluating different CNN architectures—such as AlexNet, VGG16-TL, InceptionV3-TL, Squeeze Net, and ResNet variants—have shown that deeper networks generally achieve higher classification accuracy, particularly in mixed dentition stages [43,44]. Consequently, while AI cannot replace clinician expertise, it serves as a reliable adjunctive tool that enhances diagnostic consistency, reduces variability, and supports early intervention strategies.

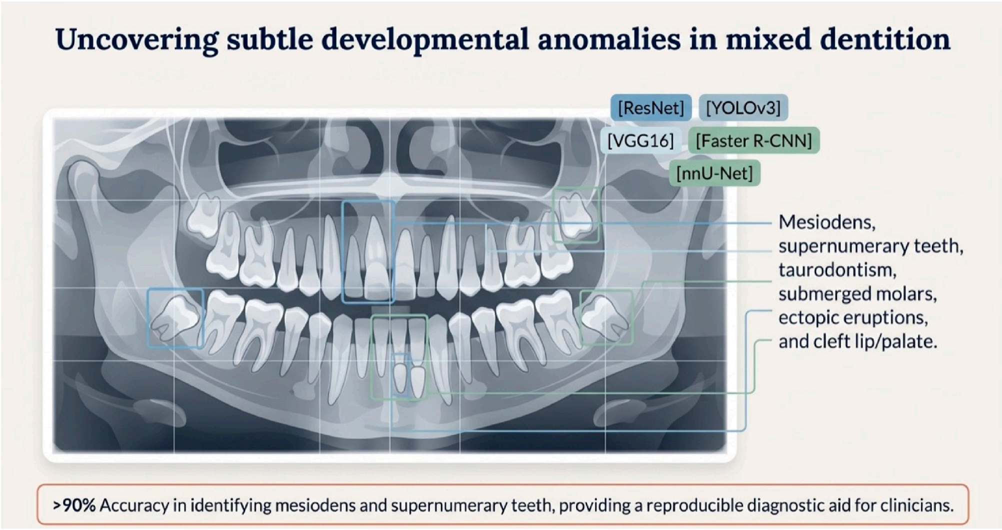

Figure 3. Identification of dental anomalies in diagnostic images or radiographs.

4.4. Orthodontics, Growth, and Skeletal Development

Among all domains of pediatric dentistry, orthodontics represents the field in which AI applications have been most extensively investigated. This is largely attributable to the data-intensive nature of orthodontic diagnosis, which relies on the integration of clinical, radiographic, and developmental information [45]. Traditional orthodontic assessments are often time-consuming and subject to inter-operator variability. In this context, AI-based systems provide a means to automate repetitive tasks while improving accuracy and reproducibility, thereby allowing clinicians to focus on higher-level diagnostic reasoning and treatment planning. Machine learning algorithms—including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), k-nearest neighbors (k-NN), and support vector machines (SVM)—have been successfully applied to evaluate cervical vertebral maturation (CVM) on lateral cephalograms [46]. Among these, ANN models have demonstrated particularly stable and reliable performance in determining optimal treatment timing. In addition, AI-driven systems for automated landmark identification on cephalometric and CBCT images significantly reduce human error and inter-operator variability. CNN-based approaches, such as YOLOv3 and BCNN, enable accurate localization of anatomical landmarks, while automated segmentation of jaw structures supports advanced three-dimensional analysis [47].

Another major advancement is represented by automated cephalometric tracing. Compared to manual methods, AI-driven approaches achieve accuracy rates exceeding 90%, substantially reducing analysis time while maintaining high reliability [48]. However, human supervision remains necessary, particularly in cases involving head positioning errors or atypical anatomical variations, where AI performance may still be inconsistent. Beyond diagnostics, AI also contributes to clinical decision-making. Predictive models assist in determining the need for extractions and estimating arch dimensions, enabling more individualized treatment strategies [49]. Moreover, AI-powered remote monitoring platforms have demonstrated a reduction in in-office visits of approximately 33%, improving patient compliance and accessibility while maintaining treatment outcomes [50]. Importantly, AI has also enhanced the assessment of growth and skeletal development. Given the limitations of chronological age as an indicator of growth potential [51,52], AI-based systems provide automated and standardized evaluation of skeletal maturity. The cervical vertebral maturation (CVM) method, widely used to assess vertebral changes in C2–C4 and reduce additional radiation exposure, has been effectively integrated into AI models [52,53]. These approaches improve both diagnostic precision and efficiency compared with traditional manual methods [54,55].

Collectively, these applications highlight the transformative role of AI in pediatric orthodontics, where it enhances efficiency, standardization, and personalization of care while maintaining the essential role of clinician expertise.

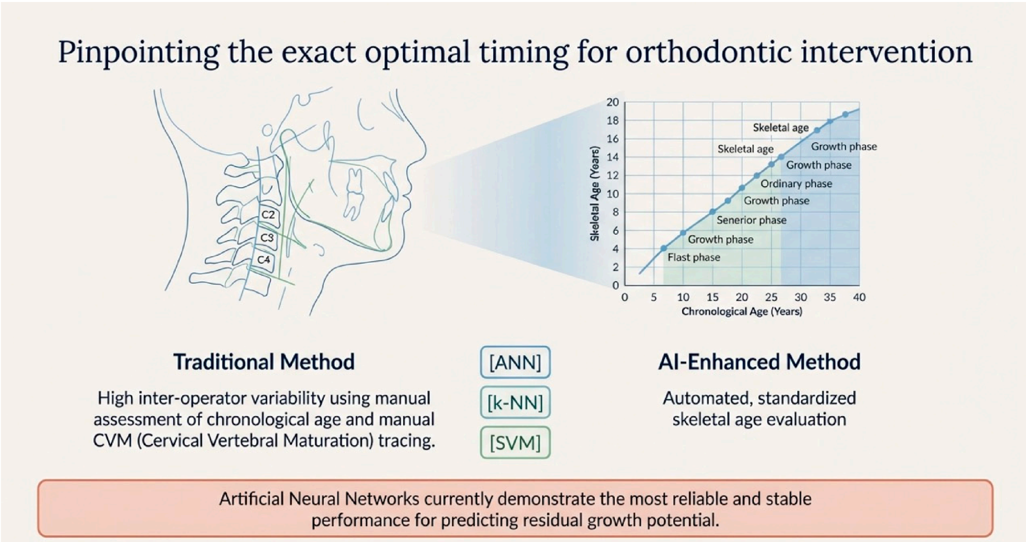

Figure 4. Interception of growth stage and skeletal development.

4.5. General Assessment and Screening Tools

Extending beyond individual patient care, AI-based technologies also offer significant potential for population-level assessment and screening. By integrating clinical, demographic, and behavioral data, these systems enable more efficient identification of high-risk pediatric populations. Deep learning models—including ANN, probabilistic neural networks, generalized regression neural networks, radial basis function networks, and multilayer perceptrons—have demonstrated the ability to estimate chronological age in children and adolescents using dental and skeletal indicators derived from orthopantomographic images [56]. These applications are particularly relevant for clinical, forensic, and epidemiological purposes. Additionally, machine learning-based toolkits incorporating algorithms such as Extreme Gradient Boosting and Naive Bayes classifiers can predict oral health indices and referral needs (e.g., COHSI and RFTN) based on sociodemographic and parental input data. This allows for more efficient allocation of healthcare resources and supports targeted preventive strategies. Importantly, AI systems can analyze complex interactions among socioeconomic status, dietary habits, oral hygiene behaviors, and access to care—relationships that are often difficult to capture using traditional statistical models [57]. This capability enables more accurate risk stratification and supports the development of community-level preventive programs. The integration of AI into school-based and public health initiatives further enhances its potential. Automated image-based screening systems combined with mobile health platforms allow large-scale, low-cost data collection and real-time analysis, facilitating early identification of children requiring professional intervention. Furthermore, AI-driven decision-support systems can prioritize referrals based on urgency and treatment needs, reducing delays in care and improving clinical outcomes. Despite these advantages, challenges remain, including issues related to dataset representativeness, generalizability, and ethical considerations. Therefore, careful validation and standardization are required before widespread implementation.

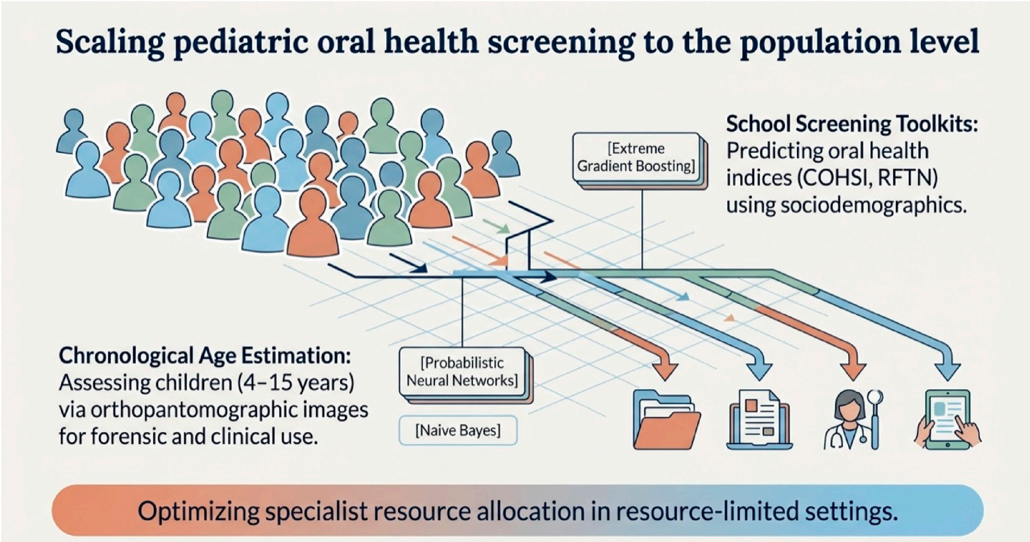

Figure 5. Scheme of AI-based screening tools.

4.6. Generative Artificial Intelligence and Chatbots

In addition to analytical AI systems, recent years have witnessed the emergence of generative artificial intelligence and chatbot-based platforms, which introduce new possibilities for communication and education in pediatric dentistry. These systems have demonstrated the ability to provide coherent and contextually relevant responses to general parental queries, particularly in areas such as trauma management, oral habits, and preventive care, where they tend to achieve higher reliability scores [58,59]. However, their diagnostic accuracy remains limited, especially in complex clinical scenarios requiring nuanced reasoning, such as the interpretation of dental anomalies or systemic conditions [60]. This limitation is largely attributable to the dependence of model performance on query specificity and contextual complexity [61]. A critical concern is the phenomenon of "hallucinations," whereby AI systems generate plausible but incorrect or non-evidence-based information. In pediatric dentistry, this represents a significant risk, particularly when caregivers rely on such outputs without professional validation. For instance, recent evaluations have identified cases where chatbots provided incomplete dental trauma management protocols [62], such as omitting critical information regarding extra-oral time or the appropriate storage media for an avulsed tooth. In another clinical scenario, some generative models have been found to recommend systemic antibiotic therapy for localized dental abscesses without signs of systemic involvement [63]. Such recommendations contradict current evidence-based guidelines and pose a risk of promoting antibiotic resistance in pediatric patients. Furthermore, generative AI lacks the ability to fully integrate patient-specific clinical context, including medical history, behavioral factors, and subtle diagnostic cues. As a result, these systems cannot currently function as independent diagnostic tools. Conversely, AI-driven educational platforms and intelligent tutoring systems represent a promising application. By delivering personalized, age-appropriate content and incorporating gamification strategies, these tools can improve patient engagement, reduce anxiety, and promote long-term oral health behaviors [63]. Hybrid approaches combining generative AI with validated clinical databases and rule-based systems are also being explored to improve reliability and ensure adherence to evidence-based standards. Overall, while generative AI

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holds potential as a communication and educational tool, its use must remain under strict professional supervision.

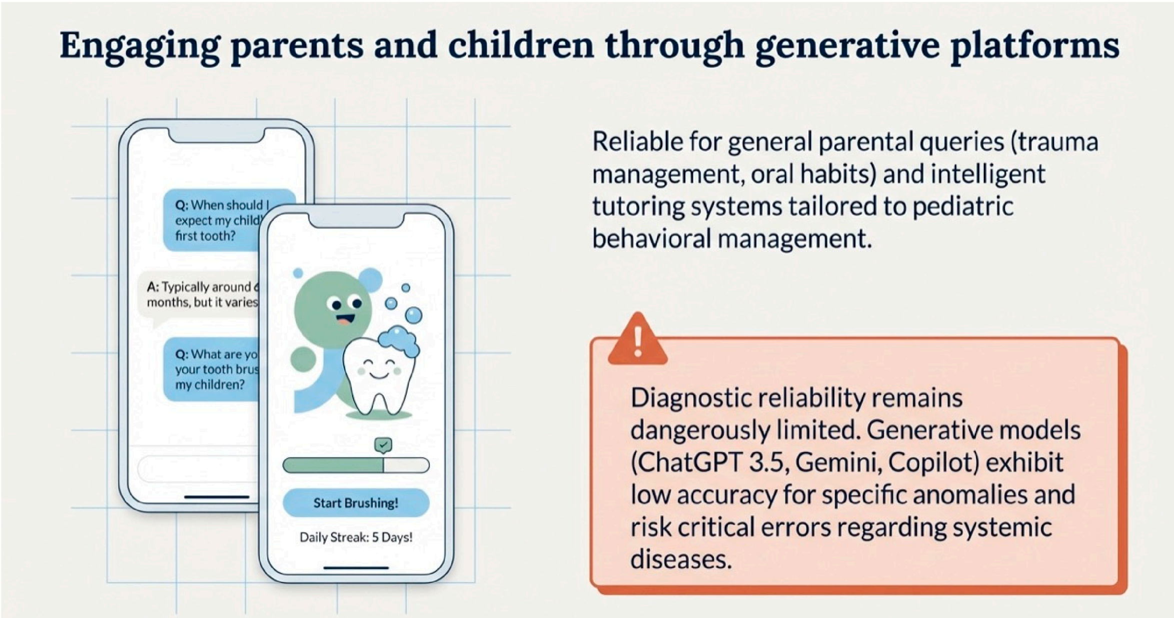

Figure 6. Usability of Generative Artificial Intelligence and Chatbots for patients.

4.7. Ethical Considerations and Future Directions

AI systems can process vast amounts of patient data; however, they carry inherent risks of privacy breaches. While encryption and secure storage are essential, achieving full confidentiality is challenging, especially given the frequent sharing of data across different platforms and institutions [62,63]. Beyond data security, a critical appraisal of AI performance metrics is necessary. Despite reports of accuracy exceeding 90%, most existing studies in pediatric dentistry rely on small, homogeneous datasets, which may lead to overfitting [64]. This phenomenon occurs when a model performs exceptionally well on training data but fails to generalize to the high variability of real-world clinical scenarios, such as diverse skeletal maturity stages or different radiographic equipment. Furthermore, the risk of algorithmic bias remains a significant concern; if training sets are not representative of diverse pediatric populations, the resulting tools may lack external validation and clinical reliability [65]. This may lead to skewed results that do not reflect the needs of all patients, potentially reinforcing existing inequalities in healthcare access and quality.

To mitigate these risks, future research should prioritize multi-centric studies and the use of "explainable AI" (XAI) to ensure that these technologies are not only accurate but also transparent [63]. Clear accountability frameworks and standardized ethical guidelines for AI in dental care are essential. Such measures will ensure both patient safety and professional responsibility, allowing for a balanced integration of technology and clinical expertise in the pediatric context.

4.8. New Fields of Applications of AI in Pediatric Dentistry

Beyond the currently established applications, several emerging domains are expected to further expand the role of artificial intelligence in pediatric dentistry. These areas, although still relatively underexplored, are likely to shape future models of care. One promising direction involves personalized treatment planning, where AI systems integrate multimodal data—including radiographic findings, clinical records, and patient-specific variables—to support individualized therapeutic strategies. Predictive analytics may further enable clinicians to simulate treatment outcomes and optimize decision-making processes. Advances in tele-dentistry and virtual assistance are also expected to enhance access to care, particularly for underserved populations. AI-driven remote monitoring platforms may facilitate continuous follow-up, early detection of disease progression, and improved continuity of care. Behavioral management represents another emerging field of interest. Machine learning models may be developed to predict anxiety patterns and tailor communication strategies, while systems integrated with biometric sensors—such as heart rate variability or facial expression analysis—could provide real-time feedback on patient stress levels. Additionally, the integration of AI with virtual reality (VR) and augmented reality (AR) technologies offers innovative approaches to reducing dental anxiety and improving patient cooperation. These systems can create personalized, immersive environments adapted to the child's emotional and cognitive profile, potentially enhancing treatment acceptance [66,67]. Another promising direction is the development of AI-integrated wearable devices and biosensors capable of continuously monitoring oral health parameters, including salivary biomarkers, pH levels, and parafunctional habits. These technologies may enable real-time risk assessment and highly personalized preventive strategies [68].

Finally, AI-driven educational platforms have the potential to transform pediatric oral health education by delivering adaptive, interactive content tailored to the child's learning style, while also supporting caregivers in reinforcing preventive behaviors. Despite these promising perspectives, several challenges remain, including the need for large, high-quality datasets, validation in real-world pediatric populations, interoperability with existing healthcare systems, and compliance with ethical and regulatory standards. Overall, these emerging applications highlight the potential of AI not only as a diagnostic and analytical tool but also as a means to enhance personalization, accessibility, behavioral management, and patient engagement in pediatric dentistry.

To ensure full transparency regarding the hierarchy of evidence, it must be noted that this study is based on an exclusive inclusion of review literature. This secondary synthesis lacks direct analysis of primary Level 1 data; therefore, the conclusions should be viewed as a comprehensive overview of existing literature rather than a direct evaluation of primary clinical outcomes.

5. Conclusions

In conclusion, AI tools demonstrate significant potential as supportive diagnostic aids in pediatric dentistry, particularly in caries detection and orthodontic planning. While current evidence highlights high levels of concordance between AI algorithms and expert clinicians, these technologies should be viewed as complementary resources rather than replacements for professional judgment. The transition from experimental performance to routine clinical implementation requires further high-quality primary studies and standardized validation protocols to ensure safety and reliability in the management of the pediatric patient.

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Data Availability Statement: Data are available upon request to the corresponding author.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. SANRA Criteria of the present review.

SANRA Criteria	Score	Scoring Reason
1. Importance for the readership	2	The introduction contains all the elements needed to explain the significance of the communication deficits of individuals
2. Stated aims or research questions	2	The aims of the study are stated clearly in the abstract and Section x with main research questions and subobjectives.
3. Description of the literature search	2	A transparent, structured search is described. The databases, keywords, Boolean operators, date range, inclusion/exclusion criteria, and the use of Kable's 12-step method are noted.
4. Referencing	2	2 Up-to-date, relevant, and peer-reviewed references were used from Databases.
5. Scientific reasoning	2	The discussion was developed by synthesizing the findings across all studies and supported with citations and any possible evidence.
6. Appropriate presentation of data	2	The results were described, generating three domains according to emerging recommendations available in the literature.

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