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Review

Machine Learning for Child Oral Health: A Scoping Review

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Abstract: Background: Machine learning (ML) has potential to assist dental professionals with diagnosing and predicting outcomes of oral health. Tooth decay in children is the most common chronic childhood disease and it can be prevented by early detection. We aim to provide a map of the current evidence on ML in child oral health and provide insight for future research. Methods: A scoping review used databases like Medline, Web of Science, EBSCO Dentistry & Oral Science Source, Cochrane Library, and Scopus. Included studies assessed ML models for diagnoses, prediction, or management of oral health in children (0–9 years). Data extraction included publication year, location, age, sample size, disease, study type, and ML algorithms. Results: a total of 29 studies were included, mainly in pediatric dentistry and dental public health. Study designs comprised cross-sectional (34.5%), cohort (31.0%), case-control (20.7%), clinical trials (10.3%), and descriptive surveys (3.5%). The majority of studies were from high-income (69.0%) and upper middle-income countries (27.6%), with a small representation from low middle-income countries (3.4%). ML focused on predicting and diagnosing oral health issues such as caries progression and risk, with neural networks predominantly tested alongside emerging techniques like random forest, regression, and gradient boosting. Conclusions: ML algorithms hold promise in improving dental diagnosis and prediction accuracy, benefiting dental professionals, including pediatric and general dentists, in enhancing proficiency and reducing clinical errors.

Keywords: machine learning; child oral health; dental diagnosis

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Citation: Mohajeri, A.; Schlaud, S.; Spector, S.; Hung, M. Machine Learning for Child Oral Health: A Scoping Review. *Appl. Sci.* **2024**, *14*, 11073. https://doi.org/10.3390/app142311073

Academic Editors: Hyoseol Lee and Mi Sun Kim

Received: 7 November 2024
Revised: 22 November 2024
Accepted: 27 November 2024
Published: 28 November 2024

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1. Introduction

Oral health is essential to overall well-being, influencing daily activities like eating, speaking, social interactions, and appearance [1]. Recognizing its profound effect on individuals' lives, the World Health Organization has listed oral health as a major global public health concern [2]. Dental caries affect 60–90% of children globally and nearly all adults, while about 30% of individuals aged 65–74 have lost all their natural teeth [3].

One of the primary objectives in managing dental caries and other oral diseases is for practitioners to rapidly assess disease severity and select optimal treatments based on individual patient needs. Early intervention is essential to minimize patient discomfort and prevent further oral health deterioration. Traditional medical imaging techniques, such as X-rays for localized examinations and CT scans for panoramic views, are crucial in diagnostic evaluations, offering dentists detailed visual insights into oral structures [4,5]. In addition to these, modern imaging tools, including intraoral cameras [6,7] and optical coherence tomography [8,9], provide real-time, non-invasive views of intraoral surfaces and tissues, aiding in early detection and ongoing monitoring of treatment effectiveness.

Artificial intelligence (AI) has become an essential tool in enhancing these diagnostic capabilities [10]. Within AI, machine learning (ML) plays a particularly significant role. ML refers to algorithms that allow computers to analyze large datasets, identify patterns, and continually improve their predictive capabilities through experience, without being explicitly programmed [11]. It generalizes from training data to make predictions on new inputs, adapting as new data become available. In the context of dentistry, ML's ability to

process and analyze vast amounts of complex data, such as patient records, radiographs, clinical images, and procedural information, makes it an indispensable tool for diagnostic insights, treatment planning, and predictive modeling [12].

In pediatric dentistry, the early detection and management of conditions like early childhood caries (ECC), malocclusion, dental trauma, and periodontal diseases are crucial. ECC, a significant public health issue in children under six years of age, can have long-term impacts on oral and systemic health if left untreated. Malocclusion, a misalignment of teeth or jaws, can affect aesthetics, speech, and function, often requiring early orthodontic intervention. Similarly, dental trauma, prevalent in active young children, necessitates prompt diagnosis and management to prevent complications like tooth loss or pulp necrosis. Periodontal conditions, though less common in children than adults, can manifest as gingivitis or aggressive periodontitis, particularly in specific high-risk groups, and demand early identification to ensure effective management.

Traditional diagnostic methods, often relying on visual–tactile examinations and radiography, may not provide comprehensive insights or predictive capabilities for these diverse conditions. ML offers transformative opportunities to enhance diagnostic precision, improve risk stratification, and tailor treatment plans across various pediatric oral health concerns. For instance, ML models can integrate data from intraoral imaging, radiographs, and patient records to predict orthodontic treatment needs, assess trauma severity, and monitor periodontal health [13]. These capabilities enable earlier interventions, personalized care strategies, and better long-term outcomes for pediatric patients.

ML applications have expanded to different dental specialties, offering diagnostic and prognostic tools that enhance clinical decision making [14]. Numerous studies [15–18] have employed ML models to predict risk factors, with some focusing on pediatric populations, while others, like Hung et al. [18], explored root caries prediction in adults. Furthermore, ML offers significant support to dental professionals in detecting and diagnosing conditions promptly and accurately, predicting outcomes, identifying at-risk individuals, standardizing care, and reinforcing clinical findings [13]. Specific applications include evaluating development and growth of a child to aid in orthodontic diagnosis [19], recognizing early signs of dental pathology [20], evaluating dental plaque levels [21], and identifying teeth such as supernumerary [22], deciduous, and permanent [23]. The integration of ML tools aligns with the profession's core focus on patient education, paving the way for preventative and predictive dentistry, ultimately elevating the standard of care. Within the ML domain, deep learning, employing multilayered neural networks, stands out as a prominent field. Notably, convolutional neural networks in deep learning have demonstrated efficacy in detecting dental caries in radiographs, offering a sophisticated approach to image analysis [24]. Research suggests that artificial neural networks (ANNs) can improve radiographic accuracy by locating the apical foramen and identifying the working length on radiographs [25]. An in vitro study used ANN to calculate composite Vickers hardness ratios, shade, and light-curing units [26].

Early childhood, defined by the World Health Organization as the period from prenatal development to eight years of age, is a critical window for health interventions due to its profound influence on lifelong well-being [27]. By age of eight, permanent first molars, central incisors, and lateral incisors are typically erupted, marking a crucial stage for preventive dental care [28]. This period represents a time when children are particularly vulnerable to oral conditions, and early interventions can have long-lasting impacts. The application of ML during this formative period holds immense potential for timely identification and management of dental issues, given the rapid developmental changes and the need for age-specific diagnostic and treatment approaches.

This review aims to explore ML applications within this key demographic, uniquely mapping the current literature while examining trends across countries with varying income levels. By identifying gaps in current practices and evaluating the potential of ML-based tools, this review seeks to illuminate opportunities for ML to advance pediatric

dentistry, enabling predictive and preventive care that can elevate the standard of oral health management for children.

2. Materials and Methods

2.1. Article Eligibility Criteria

With the goal of providing a map of the current evidence on ML in child oral health and providing insight for future research, a scoping review was selected. The review strictly adhered to the rigorous guidelines outlined by PRISMA [29] (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure an analytical and standardized approach in evaluating the available literature. Articles eligible for inclusion were required to center on the application of machine learning in the context of child oral health, aligning with the World Health Organization's definition, where children were defined as those aged <9 years [30]. Eligible articles needed to be peer-reviewed and published in English. Articles solely presented as abstracts or lacking full-text content were excluded. To maintain a focus on original research, review articles summarizing the existing literature were also excluded. Further, exclusion criteria included conference proceedings, opinion pieces, and letters to the editor. A comprehensive outline of inclusion and exclusion criteria for article selection is presented in Table 1.

Table 1. Inclusion and exclusion criteria for article selection.

Inclusion Criteria	Exclusion Criteria
• Peer-reviewed in English	• Articles that consisted of only abstracts without the full text
• Participants aged <9 years	• Animal studies
• Focused on ML and its application to child oral health	• Literature reviews (narrative, scoping, systematic, meta-analysis)
• Subjects must be human	• Conference proceedings
	• Letters to editors

2.2. Database Sources and Search Strategies

The initial search included the following databases: PubMed, Cochrane Library, EBSCO Dentistry & Oral Science Source, Scopus, and Web of Science. These databases were chosen for their diverse coverage, spanning scholarly articles, clinical trials, and research studies across multiple fields, enriching a diversity of sources included in the review.

Detailed search strategies and keywords employed for each database are provided in Table 2. These strategies were meticulously tailored to maximize the retrieval of relevant articles, ensuring a thorough consideration of pertinent studies.

Table 2. Database search strategies.

Database Name Database Link Search Date	Search Strategies	Number of Articles Found
PubMed https://pubmed.ncbi.nlm.nih.gov/ Searched on 1 May 2023	(“artificial intelligence”[MeSH Terms] OR (“machine learning”[Title/Abstract] OR “deep learning”[Title/Abstract] OR “supervised learning”[Title/Abstract] OR “unsupervised learning”[Title/Abstract] OR “Neural networks”[Title/Abstract] OR “Ensemble machine learning”[Title/Abstract])) AND (“oral health”[MeSH Terms] OR (“oral hygiene”[Title/Abstract] OR “dental health”[Title/Abstract] OR “dental care”[Title/Abstract] OR “oral care”[Title/Abstract] OR “dent*”[Title/Abstract] OR “ortho*”[Title/Abstract] OR “teeth”[Title/Abstract] OR “periodon*”[Title/Abstract] OR “caries”[Title/Abstract] OR “oral medicine”[Title/Abstract] OR “oral cancer”[Title/Abstract] OR “pulp*”[Title/Abstract] OR “maxil*”[Title/Abstract])) AND (“child*”[Title/Abstract] OR “infant”[Title/Abstract] OR “toddler”[Title/Abstract] OR “baby”[Title/Abstract])	141
Cochrane Library-Clinical Trials https://www.cochranelibrary.com/central Searched on 1 May 2023	“artificial intelligence” [Mesh] OR “machine learning” OR “deep learning” OR “supervised learning” OR “unsupervised learning” OR “Neural networks” OR “Ensemble machine learning” in Title Abstract Keyword AND “oral health” [Mesh] OR “oral hygiene” OR “dental health” OR “dental care” OR “oral care” OR dent* OR ortho* OR teeth OR periodon* OR caries OR “oral medicine” OR “oral cancer” OR pulp* OR maxil* in Title Abstract Keyword AND child* OR baby OR toddler OR infant in Title Abstract Keyword—(Word variations have been searched)	21
EBSCO Dentistry & Oral Science Source https://web.s.ebscohost.com/ehost/search/advanced?vid=0&sid=d943353a-2adf-4586-8c8c-1454b81a360c@redis Searched on 1 May 2023	(SU (“artificial intelligence”) OR TX (“machine learning” OR “deep learning” OR “supervised learning” OR “unsupervised learning” OR “Neural networks” OR “Ensemble machine learning”)) AND (SU (“oral health”) OR TX (“oral hygiene” OR “dental health” OR “dental care” OR “oral care” OR dent* OR ortho* OR “oral health” OR teeth OR periodon* OR caries OR “oral medicine” OR “oral cancer” OR pulp* OR maxil*)) AND (TX (child* OR baby OR toddler OR infant))	290
Scopus https://www.scopus.com/home.uri Searched on 1 May 2023	TITLE-ABS-KEY(“artificial intelligence” OR “machine learning” OR “deep learning” OR “supervised learning” OR “unsupervised learning” OR “Neural networks” OR “Ensemble machine learning”) AND TITLE-ABS-KEY(“oral health” OR “oral hygiene” OR “dental health” OR “dental care” OR “oral care” OR dent* OR ortho* OR “oral health” OR teeth OR periodon* OR caries OR “oral medicine” OR “oral cancer” OR pulp* OR maxil*) AND TITLE-ABS-KEY (child* OR baby OR toddler OR infant)	445
Web of Science https://www.webofscience.com/wos/author/search Searched on 1 May 2023	TS = (“artificial intelligence” OR “machine learning” OR “deep learning” OR “supervised learning” OR “unsupervised learning” OR “Neural networks” OR “Ensemble machine learning”) AND TS = (“oral health” OR “oral hygiene” OR “dental health” OR “dental care” OR “oral care” OR dent* OR ortho* OR “oral health” OR teeth OR periodon* OR caries OR “oral medicine” OR “oral cancer” OR pulp* OR maxil*) AND TS = (child* OR baby OR toddler OR infant)	122

2.3. Selection Process

The article selection process was rigorous and systematic to ensure the inclusion of accurate, relevant studies. Initially, a primary reviewer independently screened titles and abstracts according to predefined inclusion and exclusion criteria, documenting exclusion reasons where applicable. A secondary reviewer then independently verified these selections. Any discrepancies were resolved through discussion and consensus to ensure reliability in the selection process.

Articles that passed the initial screening underwent a detailed full-text analysis, where key information, such as sample size, age range, study design, type and purpose of ML models, dental specialty, and study outcomes, was systematically extracted. To ensure data accuracy and completeness, a secondary reviewer independently repeated the extraction. This redundancy confirmed that all relevant information was captured and allowed for the resolution of any discrepancies.

Each article was reviewed by multiple individuals to maintain high standards of quality and relevance, ensuring that only studies meeting inclusion criteria were included in the final analysis. Reviewers carefully evaluated each article's relevance to the research question. To add an extra layer of quality control, the principal investigator conducted random audits of the reviewed articles, verifying data extraction accuracy and the consistency of the review process. These independent audits helped to minimize potential biases or errors, thereby strengthening the reliability and credibility of the final analysis.

2.4. Data Synthesis and Thematic Analysis

Our data synthesis employed a thematic analysis framework to systematically analyze and integrate findings from the selected studies. The following steps outline our approach:

Familiarization with data: Reviewers independently read and re-read the extracted data to become familiar with the scope and content of the studies. Key findings related to ML models, their applications, geographic origins, economic regions, and study outcomes were noted, ensuring that the data was well understood before proceeding further.

Initial Coding: A coding framework was collaboratively developed, categorizing data by key variables: ML model type (e.g., random forest, neural networks); purpose of the model (e.g., diagnosis, prediction, management); dental specialty (e.g., pediatric dentistry, orthodontics); and economic regions (e.g., high-income countries (HIC), upper-middle-income countries (UMIC), and low-middle-income countries (LMIC) [31]). Temporal data were also coded to track trends over decades.

Searching for themes: The codes were grouped into broader categories to identify common themes. These themes included global disparities in ML adoption, temporal trends, predominant ML models in dental specialties, and identified research gaps.

Reviewing and refining themes: The identified themes were reviewed by multiple reviewers to ensure they accurately reflected the underlying data. Overlapping or redundant themes were merged, while underdeveloped themes were clarified with additional data.

Integrating findings: These themes were applied to organize the results focusing on the geographic distribution, economic disparities, and temporal trends in ML adoption. This thematic approach helped organize and interpret the data in a way that highlighted critical areas for further exploration.

Validation and reliability: Independent reviews and random audits ensured consistency and reduced bias.

3. Results

Out of the initially identified 1019 articles, following rigorous application of inclusion and exclusion criteria as outlined in Table 1, 235 duplicates were removed, resulting in a total of 784 articles. The screening of titles and abstracts for 784 articles resulted in the exclusion of 750 for the following reasons: 151 were literature reviews; 96 were editorials, abstracts, or conference papers; 14 were not written in English; 130 were unrelated to the ML field; 180 did not focus on oral health; and 179 were not targeted at children under 9 years.

This process left 34 articles for full-text review, where an additional 5 were excluded; 2 for being unrelated to ML and 3 for not targeting children under 9 years. Ultimately, 29 studies met all inclusion criteria and were included in the final review (Figure 1). Table 3 provides detailed information on the included studies, while Table 4 summarizes key findings.

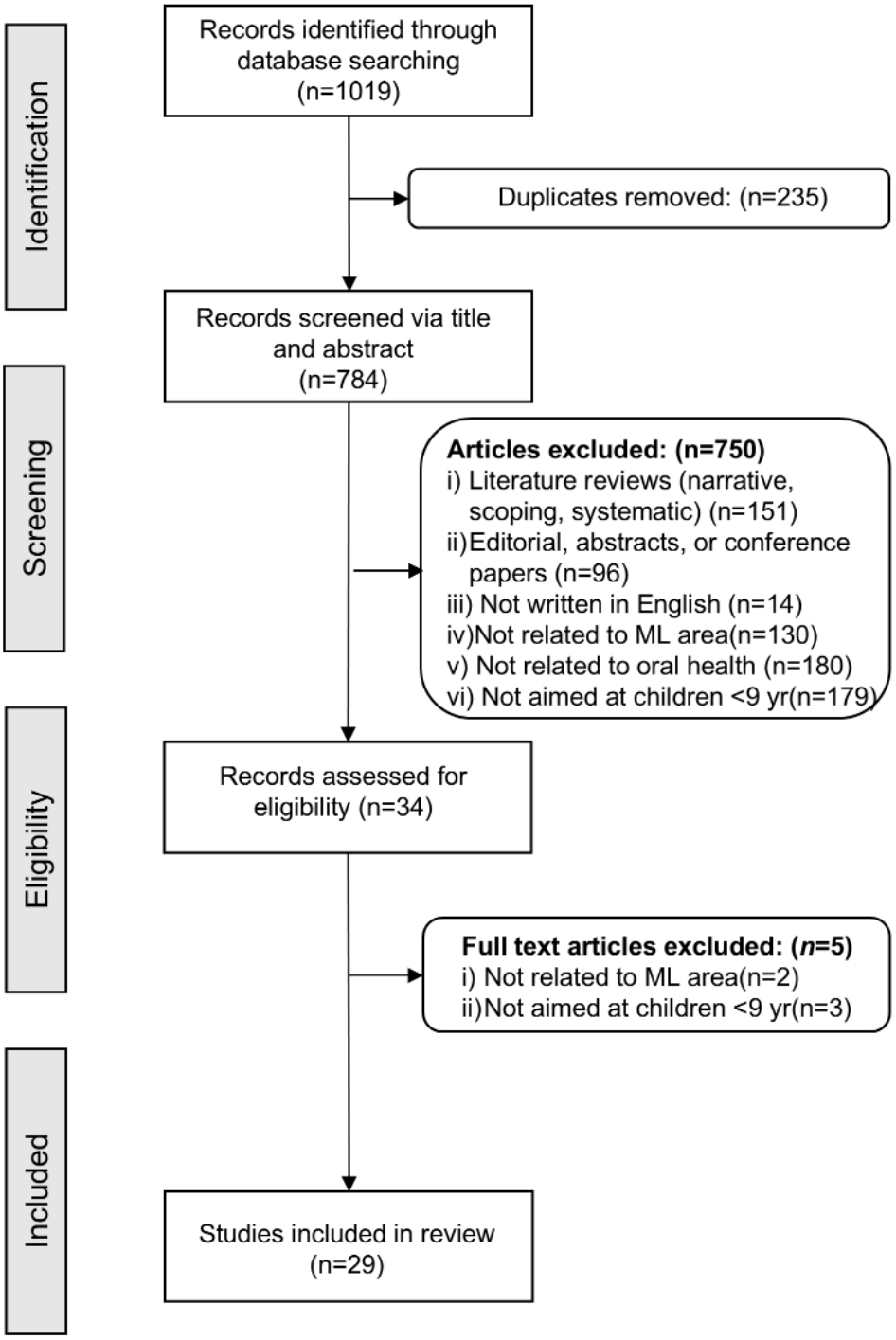


Figure 1. Study selection.

Table 3. Detailed overview of included studies.

Author (Year)	Country	Dental Specialty	Sample Size	Age Range	Purpose of the Model	ML Model Utilized	Outcome
Grier et al. (2021) [32]	USA	Dental public health	189	1–3 years old	Prediction	Random forest and gradient boosting classifiers	A total of 36 children developed ECC, 20 remained caries-free. Saliva microbiota with machine learning shows promise for accurate CRA in caries-free children.
Al Kheraif et al. (2019) [33]	Saudi Arabia	Dental public health	1000	5 years old	Prediction	Neural network	The Ruzzo–Tompa neural network achieved 99.22% accuracy in identifying abnormal dental features, with a 1.2% misclassification rate.
Nowak et al. (2020) [34]	USA	Pediatric	2009	18 months old to 4 years old	Prediction	Natural language processing techniques, regression procedures	Age at the first dental visit predicted caries risk (odds ratio per year: 2.11). High-risk factors included breastfeeding status, non-English language, and over 20% no-show rates. A first visit at 18 months showed a 42% caries risk, rising to 83% if delayed until age four. Model validation matched expected performance.
Woodsend et al. (2022) [35]	UK	Orthodontist	239	5 years old	Diagnosis	Deep learning	The ALR software identified the correct teeth in 79.7% of models, reducing human error in both deciduous and permanent dentitions.
Saxena et al. (2008) [36]	USA	Pediatric	39	2.4–8.6 years	Diagnosis	Support vector machine and neural network	The study used 49 S. mutans genotypes. S-ECC cases had a single genotype, revealing genetic differences that AI can use to classify CF or S-ECC.
Karhade et al. (2021) [37]	USA	Dental public health	6404	3–5 years old	Prediction	Deep learning	A machine learning model using age and parental perception can accurately estimate ECC probability and classify ECC status based on demographic data.
Ganiatsou (2023) [38]	Greece	Forensic dentistry	51	3.5 and 9 years old	Diagnosis	Clustering method	Of 51 individuals, 45 were breastfed for one to three years; five had shorter or no breastfeeding. The diet included animal protein and C3 plants, with increased small fish and C4 plants from the Roman period. Machine learning identified nine individuals with potential physiological stress related to breastfeeding patterns.
Ramos-Gomez et al. (2021) [17]	USA	Pediatric	182	2–7 years old	Prediction	Random forest	Machine learning algorithms predicting dental caries help clinicians educate patients on oral hygiene and diet, demonstrating effective prevention strategies.

Table 3. *Cont.*

Author (Year)	Country	Dental Specialty	Sample Size	Age Range	Purpose of the Model	ML Model Utilized	Outcome
Peng et al. (2021) [39]	USA	General	24,223	6–60 months	Diagnosis	Clustering method	Early decay patients had the highest dental and medical costs, while those with regular preventive care had the lowest. A third of early decay patients were diagnosed with another condition within 0–24 months.
Xiao et al. (2021) [40]	USA	General	84	1–5 years old	Diagnosis	Clustering method	AICaries is a useful resource for parents for screening and early detection of ECC.
Xie et al. (2021) [41]	USA	Public health	289	3–5 years old	Prediction	Random forest	ENVIM outperformed MelonnPan in metabolite prediction across the ZOE2.0, Lloyd-Prince, and Mallick datasets, showing good performance for microbiome-based predictions and individual metabolites.
Liu et al. (2022) [42]	China	Pediatric	1480	4–9 years old	Diagnosis	Deep learning	The auto-screening system had predictive values of 0.86 and 0.88, with 90% specificity and 86% sensitivity, outperforming three pediatric dentists in detecting EE. Regular follow-ups are needed to address potential false negatives.
Zaorska et al. (2021) [43]	Poland	Pediatric	95	20–40 months	Prediction	Neural network	Carious patients had more rs10429371 TT homozygotes and T alleles, while non-caries patients had more CT heterozygotes. The GG homozygote and G allele of rs7096206 were also more common in carious patients. A neural network predicted early childhood caries with 90.9–98.4% accuracy.
Heimisdottir et al. (2021) [44]	United States	Dental public health	300	36–71 months old	Prediction	Regression, random forest, and gradient boosting classifiers.	Of 503 identified metabolites, 16 were significantly associated with ECC, with catechin and fucose among the key metabolites. The localized ECC case definition had the strongest correlation with the metabolome (dCor $p = 8 \times 10^{-3}$), providing insights for risk assessment.
Koopaie et al. (2021) [45]	Iran	Dental public health	40	48–72 months	Prediction	neural networks, gradient boosting classifiers, decision tree, Random Forest, Support vector machine	This study links cystatin S protein to dental caries in children aged 48–71 months, showing significant relationships with ECC risk factors and salivary levels through statistical analysis and machine learning.

Table 3. *Cont.*

Author (Year)	Country	Dental Specialty	Sample Size	Age Range	Purpose of the Model	ML Model Utilized	Outcome
Quivey et al. (2021) [46]	USA	Pediatric	56	1–3 years	Prediction	Random forest and gradient boosting classifiers	*Corynebacterium* sp., *Selenomonas* sp., *Kingella* sp., *Veillonella parvula*, and unidentified Pseudomonas were abundant in caries. Random forest and gradient boosting classifiers distinguished ECC onset from caries-free, with random forest at 85.5% accuracy.
Raksakmanut et al. (2023) [47]	Thailand	Pediatric	30	1 year old	Prediction	Random forest	Low levels of Prevotella nanceiensis and other bacteria in 1-year-olds are linked to caries by 12 months. Salivary microbial biomarkers can accurately predict caries in this age group.
Montenegro et al. (2008) [48]	Brazil	Pediatric	3864	Less than 5 years old	Prediction	Decision trees, MLP neural networks, kNN, support vector machines	MLP neural networks achieved the best caries prediction with a 22.75% error rate. Feature selection decreased performance for MLP and SVM but improved it for decision trees and kNN.
Ichimura et al. (2018) [49]	Japan	Pediatric	5	4–6 years old	Diagnosis	Deep learning and neural networks	Deep learning accurately identifies brushing points using a smartphone's geometric sensor, showing if a child brushes properly.
Li et al. (2021) [50]	China	Public health	130	6–8 years old	Prediction	Random forest	Geography influences salivary microbiota, predicting origin cities nearly 100% accurately. A model with fourteen bacterial species diagnoses caries with 83.08% accuracy (AUC, 92.17%), suggesting universal caries diagnosis potential.
Wu et al. (2022) [51]	Thailand	Pediatric	177	3 year olds	Prediction	Linear discriminant analysis, random forest, and regression model	Caries rates increase with pre-chewed food. Vaginally born children had more caries. Over 83% of ECC children had high S. mutans levels. Caries-free children used fluoridated toothpaste and consumed fewer sweets. S. mutans, P. histicola, and L. hongkongensis were identified as caries-promoting species.
Hart et al. (2011) [52]	Brazil	Dental public health	204	1–8 years old	Prediction	Random forest	Models combining microbial and proteomic data outperform single-source models, improving accuracy for caries classification. The best model achieved a 6% test error, >92% sensitivity, and >95% specificity.

Table 3. *Cont.*

Author (Year)	Country	Dental Specialty	Sample Size	Age Range	Purpose of the Model	ML Model Utilized	Outcome
de Jesus et al. (2021) [53]	Canada	Pediatric	80	<72 months of age	Prediction	Regression algorithms and random forest	Streptococcus mutans was more abundant in dental plaque of S-ECC children, while Candida dubliniensis and C. tropicalis were higher in their oral swabs compared to caries-free controls.
de Jesus et al. (2020) [54]	Canada	Pediatric	80	<72 months of age	Diagnosis	Random forest	Sex may influence the microbial composition of supragingival plaque in caries-free children versus those with S-ECC, suggesting unique biomarkers for S-ECC in males and females.
You et al. (2020) [55]	China	Pediatric	86	5–8 years old	Diagnosis	Conventional neural network	The AI model identified dental plaque better than pediatric dentists in high-resolution photos, but both performed equally in lower-resolution intraoral photos.
Qu et al. (2022) [16]	China	Pediatric	481	12–60 months	Prediction	Random forest, and logistic regression	The caries risk model for Chinese children under 60 months ranked RF highest, followed by LR and Adaboost.
Park et al. (2021) [15]	Republic of Korea	Pediatric	4195	1–5 years	Prediction	Random forest, regression algorithms and gradient boosting classifiers, and decision tree	ECC risk is low for children brushing $\geq$ 3 times daily and high if mothers have a DMFT score $\geq$ 7. Key factors include older age, low income, infrequent brushing, and maternal age $\geq$ 35. All models had AUROC > 0.7, showing no clear superior method.
Tamaki et al. (2009) [56]	Japan	General	560	5–6 years old	Prediction	Neural network model	Out of 500 subjects, 74 developed new caries. High S. mutans and S. sobrinus levels, along with salivary pH and gender, predicted caries risk. Neural networks were more effective than logistic regression.
Yan et al. (2022) [57]	China	General	2903	7 years old	Diagnosis	Deep learning	Accuracy of molar identification of the newly made model in this study was 98.5%, and the tooth classification accuracy was 85.6%.

Table 4. Summary of key findings.

No	Dental Specialty	Articles n (%)	Economic Region (HIC, UMIC, LMIC)	Ages Min–Max	Category of ML Model n (%)	Type of ML Model n (%)	Study Design n (%)
1	Pediatric	15 articles (51.7%)	HIC = 10 (66.7%) UMIC = 5 (33.3%) LMIC = 0 (0%)	1 year old–9 years old	Diagnosis = 5 (33.3%) Prediction = 10 (66.7%) Management = 0 (0%)	Neural network (5) = 17.9% Random forest (8) = 28.6% Linear discriminant (1) = 3.6% Regression model (5) = 17.9% Support vector machine (2) = 7.1% Gradient boosting (2) = 7.1% Ensemble methods (1) = 3.6% Natural language processing (1) = 3.6% Decision tree (1) = 3.6% Deep learning (2) = 7.1%	Case control (4) = 26.7% Cross-sectional (6) = 40% Cohort (4) = 26.7% Clinical trial (1) = 6.7%
2	General	4 articles (13.7%)	HIC = 3 (75%) UMIC = 1 (25%) LMIC = 0 (0%)	6 months old–6 years old	Diagnosis = 3 (75%) Prediction = 1 (25%) Management = 0 (0%)	Clustering method (2) = 50% Deep learning (1) = 25% Neural network (1) = 25%	Cross-sectional (1) = 25% Descriptive survey (1) = 25% Cohort (2) = 50%
3	Orthodontics	1 articles (3.5%)	HIC = 1 (100%) UMIC = 0 (0%) LMIC = 0 (0%)	5 years old	Diagnosis = 1 (100%) Prediction = 0 (0%) Management = 0 (0%)	Deep learning (1) = 100%	Cross-sectional (1) = 100%
4	Dental public health	8 articles (27.6%)	HIC = 5 (62.5%) UMIC = 2 (25%) LMIC = 1 (12.5%)	1 year old–8 years old	Diagnosis = 0 (0%) Prediction = 8 (100%) Management = 0 (0%)	Random forest (6) = 42.9% Neural network (2) = 14.3% Gradient boosting (3) = 21.4% Support vector machine (1) = 7.1% Deep learning (1) = 7.1% Regression algorithm (1) = 7.1%	Cohort (3) = 37.5% Case-control (2) = 25% Clinical trial (1) = 12.5% Cross-sectional (2) = 25%
5	Forensic	1 article (3.5%)	HIC = 1 (100%) UMIC = 0 (0%) LMIC = 0 (0%)	Birth–9 years old	Diagnosis = 1 (100%) Prediction = 0 (0%) Management = 0 (0%)	Clustering method (1) = 100%	Clinical trial (1) = 100%

3.1. Dental Specialties and Study Characteristics

The included studies were categorized across five different dental specialties: pediatric, general, orthodontics, dental public health, and forensic (Table 4). Notably, ML algorithms were predominantly tested in conditions related to pediatric dentistry (51.7%), followed by dental public health (27.6%) and general dentistry (13.7%). The purpose of the ML models was also categorized into prediction, diagnoses, and management, with prediction (65.5%) and diagnosis (34.5%) being the most common applications of ML algorithms in these studies. Within pediatric dentistry, a strong emphasis was placed on predictive models (66.7%), utilizing common machine learning models such as neural networks (17.9%) and random forests (28.6%). General dentistry studies focused primarily on diagnostics (75%) and predictive (25%) applications, employing clustering methods (50%), deep learning (25%), and neural networks (25%). All studies in dental public health (27.6%) concentrated on prediction, with random forests (42.9%) and gradient boosting (21.4%) as the preferred models. Orthodontics and forensic dentistry each accounted for 3.5% of the studies, with orthodontics exclusively employing deep learning for diagnosis, while forensic dentistry utilized clustering methods for diagnostics.

3.2. Study Design and Participant Characteristics

The predominant study designs were cross-sectional studies (34.5%), followed by cohort studies (31.0%) and case-control studies (20.7%). The age range of participants varied, with most studies conducted on participants aged 1 to 6 years (72.4%), and a significant portion specifically focused on pediatric (57.1%) (Table 4). Additionally, most studies reported sample sizes below 300 (65.5%), with only 20.7% exceeding a sample size of 2000 participants.

3.3. Global Distribution and Economic Regions

Geographically, the Americas contributed the highest number of studies (51.7%), followed by Asia (37.9%), with Europe making the least contribution (10.3%) (Figure 2). HICs dominated the literature (69.0%), particularly in categories of ML models such as prediction (60.0%) and diagnostics (40.0%). UMICs contributed 27.6%, mainly focusing on prediction (75.0%) and diagnostics (25.0%). LMICs made the smallest contribution (3.4%), solely in the domain of prediction (Figures 2 and 3).

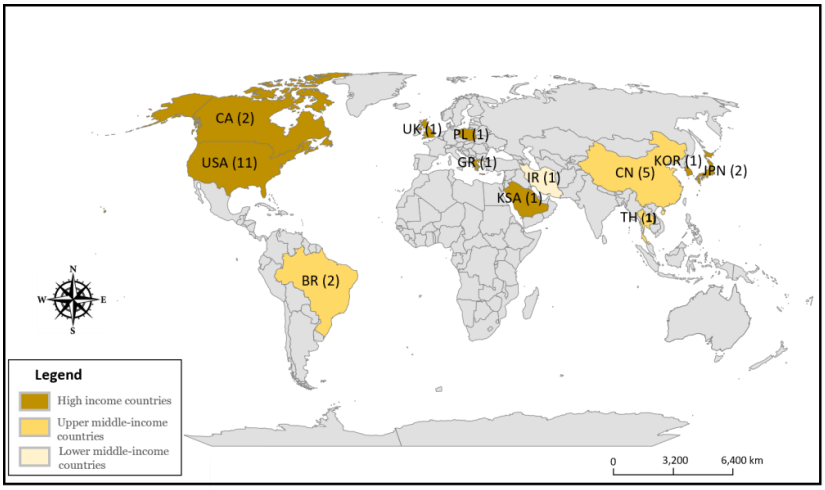


Figure 2. Global distribution of publications on child oral health using machine learning, categorized by country income levels. High-income countries (dark gold) such as the USA, Canada, and parts of Europe demonstrate the highest research output. Upper-middle-income countries (medium gold), including China and Brazil, show moderate contributions, while lower-middle-income countries (light gold), such as Iran, reflect emerging research activities. The map highlights disparities in research productivity based on income levels, with a compass rose and scale bar for spatial reference.

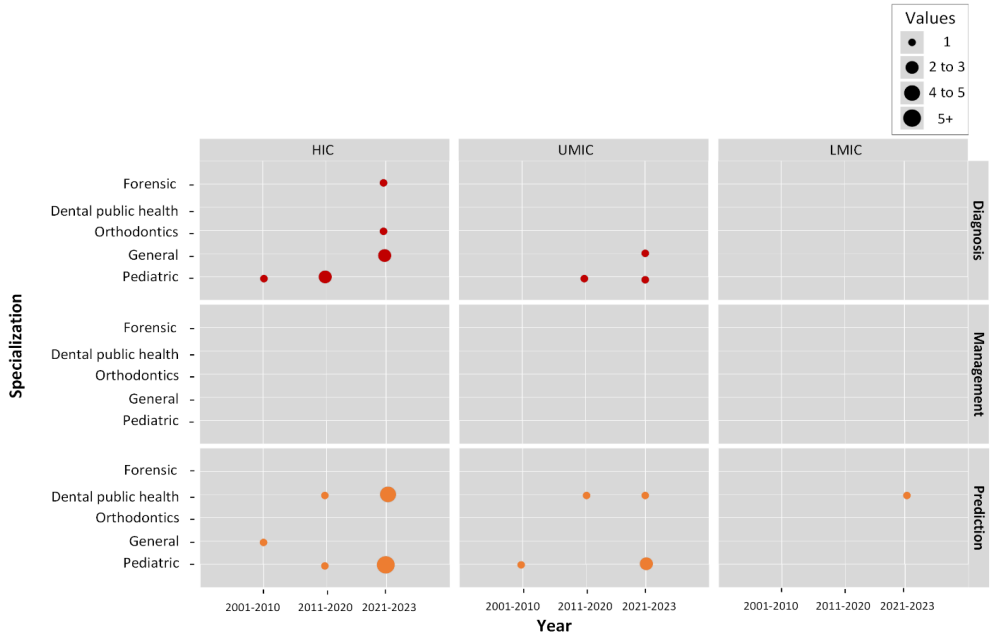


Figure 3. Trends in the use of machine learning (ML) for diagnosis, management, and prediction in dentistry across income groups (HIC: high-income countries, UMIC: upper-middle-income countries, LMIC: lower-middle-income countries) from 2001–2023. The size of the circles represents the number of studies, while the colors indicate the type of application: red for diagnosis and orange for prediction. Notably, high-income countries show a greater and consistent use of ML for diagnosis and prediction, particularly in recent years (2021–2023). Upper- and lower-middle-income countries exhibit increasing but less consistent adoption, with a focus on prediction in LMICs. This highlights disparities in the adoption of ML technologies across economic regions.

Table 5 highlights the variations in ML applications by economic region. HICs exhibited the most diverse range of ML models and applications, with prediction and diagnostics dominating dental specialties such as dental public health, pediatric dentistry, and orthodontics. For example, random forest, regression, neural network, and gradient boosting classifiers were commonly employed across specialties, with deep learning prominently used for orthodontic diagnosis. In contrast, UMICs focused heavily on random forests and neural networks for prediction and diagnostic tasks in pediatric and general dentistry. LMICs had the narrowest scope, primarily utilizing neural networks, decision trees, and gradient boosting classifiers for predictive tasks in dental public health.

Table 5. Application of machine learning models in dental specialties across economic regions.

Economic Region	Specialty	Purpose	Common ML Models
HIC	Dental public health	Prediction	Random forest, gradient boosting classifiers, neural network, deep learning, regression
	Pediatric	Prediction, diagnosis	Random forest, neural network, Regression, gradient boosting classifiers
	Orthodontist	Diagnosis	deep learning
	General	Diagnosis, prediction	Clustering method, neural network
	Forensic	Diagnosis	clustering method
UMIC	Dental public health	Prediction	Random forest
	Pediatric	Diagnosis, prediction	Random forest neural networks, regression
	General	Diagnosis	deep learning
LMIC	Dental public health	Prediction	Neural networks, gradient boosting classifiers, decision tree, random forest, support vector machine

3.4. Temporal Trends and Machine Learning Techniques

Over the three decades, there was an increasing trend in the use of machine learning for prediction in pediatric and dental public health, predominantly from HICs (Figure 3). In the initial decade (2001–2010), neural networks were the preferred ML algorithm (Figure 4A). Between 2011 and 2020, in addition to previously used algorithms, researchers started employing deep learning, random forest, and regression techniques. In the current decade (2021–2023), random forest and regression continued to rise, while newer techniques like gradient boosting rapidly emerged. When analyzed across dental specialties, deep learning and neural networks were commonly utilized (Figure 4B). When examined across economic regions, HICs consistently showed the most robust adoption of newer techniques, integrating gradient boosting and natural language processing for advanced applications. UMICs exhibited a gradual shift toward deep learning and decision trees, reflecting an expansion in technical capacity. LMICs, on the other hand, maintained a focus on simpler yet effective models like neural networks and decision trees, reflecting resource-driven constraints.

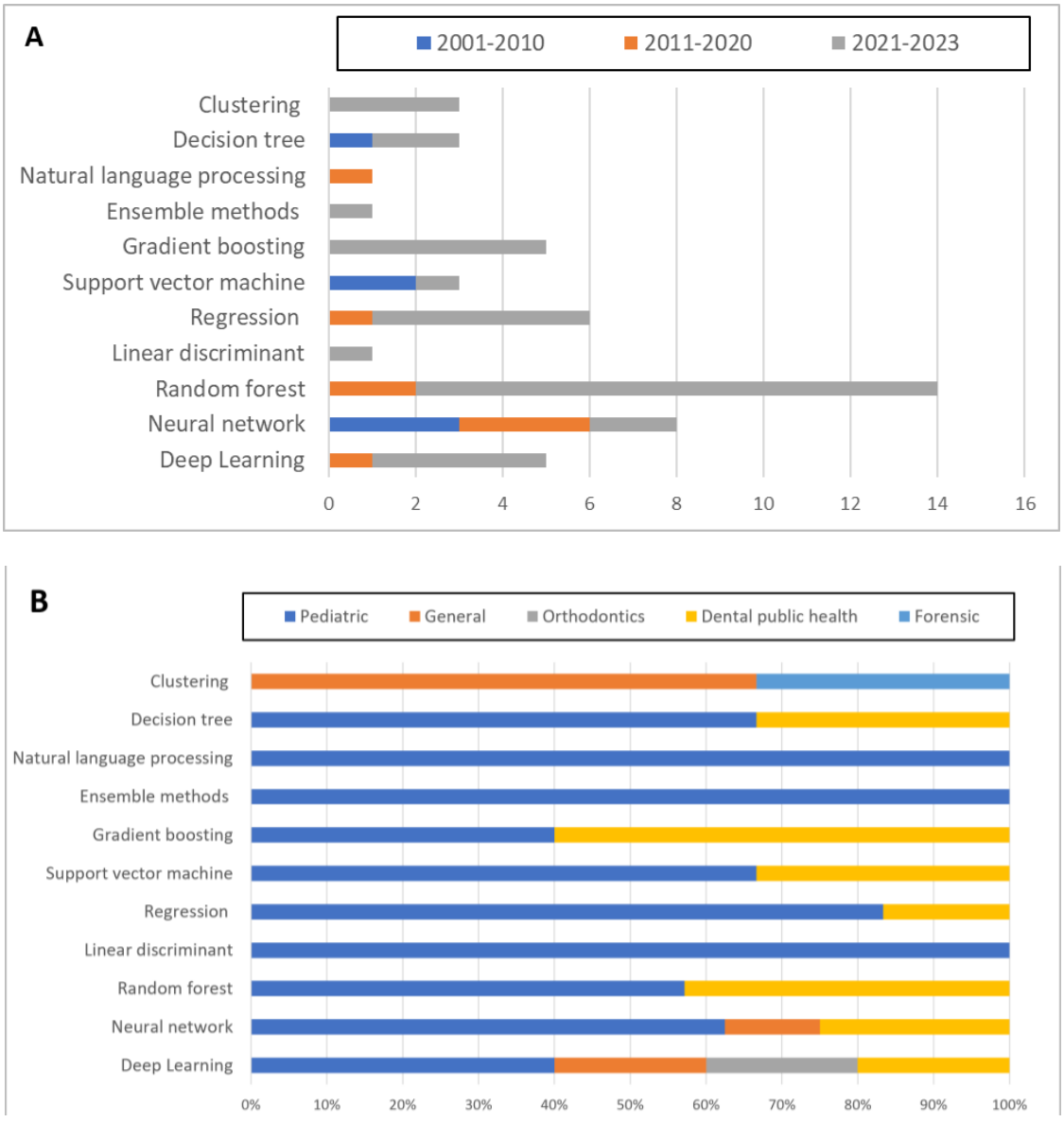


Figure 4. (**A**) Use of different ML algorithms over time. (**B**) Use of different ML algorithms according to dental specialties.

4. Discussion

This review showed that LMICs contribute the least to publications pertaining to ML for oral health diagnosing and predicting in children under 9 years of age. Throughout the literature there are many ideas pertaining to why the LMICs have low publishing rates. A cross-sectional study by Fidel Rubagumya sought to understand the participation of UMICs and LMICs in clinical trials done by HICs. In this study, it was concluded that HICs enrolled more participants in clinical trials from LMICs and UMICs [58]. This could explain the disproportion of more research completed in HIC compared to that of their counterparts due to the use of LMICs and UMICs participants in HIC. Since the HIC uses the LMIC and UMIC resources, these countries are limited in not only supply of resources such as funding, but participants as well. Although this alone could explain the result of low publication numbers for LMICs found in this review, another editorial completed by Saurab Sharma explained general barriers to which LMICs face when conducting research. A main conclusion made in that study is that these LMICs lack research funding in their national budget, in turn hindering the amount of research that can be produced [59]. LMICs can overcome this research funding disparity through the use of partnerships with HICs. Partnerships including co-funded projects or sharing of research facilities can serve as a powerful strategy to bring together complementary strengths and improve access to resources and training. If these LMICs had more budget for their nation, they would be able to gain the resources needed to complete their research.

The results of this study indicate that the USA was the predominant contributor to the publications included in our analysis. However, it is essential to consider that the restriction to studies published in English may have influenced this conclusion. Additionally, the availability of funding and resources in the USA likely facilitates a higher volume of publications. This aligns with findings from a bibliometric analysis conducted by Faris Yahya Asiri, which also identified the USA as the leading contributor in terms of dental articles included in the study [60]. Together, these insights highlight the significant role of the USA in shaping dental research trends, while also suggesting potential limitations in the scope of the analysis.

The increasing prevalence of ML algorithms in pediatric dentistry for prediction stems from their ability to assess the risk of oral health issues, anticipate the progression of conditions, and offer insights into long-term prognosis. These predictive models aid in tailoring treatment plans, guiding interventions, and optimizing resource allocation based on anticipated patient needs. By analyzing behavioral patterns, these algorithms provide valuable information for promoting preventive strategies and improving oral health habits in children. Additionally, the predictive capabilities support informed decision making by clinicians and caregivers, contributing to more personalized and effective approaches in pediatric dental care. The neural networks technique was originally the preferred ML algorithm used in research, and it has still been consistently used as time progresses. This technique is also a commonly used algorithm of ML when looking across different specialties. Neural networks are popular in their application to dentistry due to their domain largely being well adapted to the task of image classification. This technique is the most used algorithm for image recognition [61]. In dentistry, the patient exam consists of both a clinical and radiographic examination to make the appropriate conclusions and treatment plan for a patient. Numerous images and radiographs are taken at a patient exam and are stored over time to evaluate the progress of a patient. Radiographs allow a dentist to see changes in the hard and soft tissues such as caries, bone disease, infections, and tumors. In children, they also allow the dentist to evaluate if the teeth and jaw bones are developing properly and to address any concerns early on [62]. Neural networks can be used to identify all of these changes, such as caries progression, with more accuracy and efficiency than that of the clinician. The thorough analysis of these images by clinician is time consuming and laborious leading to the possibility of some conditions going undiagnosed. Therefore, ML techniques such as neural networks were widely used in the articles reviewed in our paper.

The implications of this study underscore the urgent need for increased cooperation in research regarding ML applications for pediatric dentistry. The observed disparity in contributions from LHICs raises concerns regarding their knowledge and capability to progress in this field. Efforts should be directed toward overcoming barriers faced by LMICs, including limited research funding for comprehensive landscape exploration and the need for improved access to training and resources. Furthermore, establishing partnerships between HICs and LMICs could foster knowledge exchange and capacity building, enhancing local expertise.

Additionally, the prevalence of neural networks in dental diagnostics suggests the importance of leveraging image recognition technologies for more efficient and precise patient examinations. These technologies can not only streamline diagnostic processes but also enhance the accuracy of treatment planning, ultimately improving patient outcomes. Addressing these implications could contribute to seamless integration of ML in pediatric dentistry, ensuring that advancements benefit populations worldwide and help bridge the gap in healthcare disparities. By prioritizing collaboration and resource sharing, the global dental community can work toward a future where innovative technologies are accessible to all, enhancing care for children everywhere.

The study has certain limitations. Despite conducting an extensive literature search across multiple databases, the possibility of missing relevant articles cannot be entirely ruled out. This limitation highlights the inherent challenges in ensuring comprehensive coverage in scoping review. Furthermore, the deliberate narrowing of the study's scope based on age limitations restricts the inclusion of valuable information available in the broader literature, potentially overlooking important trends and insights that could inform future research.

Additionally, the exclusion of non-English language publications introduces a potential bias, as the findings may not capture diverse perspectives from regions where English is not the primary language of scientific discourse. This language-based exclusion criterion may hinder the ability to understand fully the global landscape of research in this field. By omitting insights from research conducted in countries and areas where English is not commonly used in academic discourse, the study risks underrepresenting important cultural and contextual factors that could influence research outcomes and practices.

These limitations highlight the need for future studies to adopt a more inclusive approach, potentially incorporating multi-language searches and broader inclusion criteria to ensure a more comprehensive understanding of the subject matter. By addressing these gaps, subsequent research can enhance the richness of the data and provide a more holistic view of the trends and challenges within the field.

5. Conclusions

This scoping review highlights the increasing integration of ML in pediatric dentistry, with specific applications such as early detection of childhood caries, risk assessment for orthodontic issues, and personalized treatment planning based on behavioral and imaging data. ML algorithms, particularly neural networks, have the potential to significantly enhance treatment outcomes by improving diagnostic accuracy and optimizing resource allocation. However, the adoption of these technologies faces challenges, including limited availability of robust datasets, particularly in low- and middle-income countries, and the need for clinician training to effectively utilize these tools. Addressing these limitations through increased collaboration, resource sharing, and targeted research funding is crucial to realize the full potential of ML in pediatric dentistry. As research into the use of ML for predicting and diagnosing oral health issues in children advances, we encourage researchers to deepen their exploration of its potential and implications, policymakers to prioritize investment in related research funding, and clinicians to incorporate ML tools into their clinical practice.

Author Contributions: Conceptualization, A.M. and M.H.; methodology, A.M. and M.H.; validation, A.M. and M.H.; formal analysis, A.M., S.S. (Samantha Schlaud), S.S. (Sydnee Spector) and M.H.; investigation, A.M. and M.H.; data curation, A.M., S.S. (Samantha Schlaud), S.S. (Sydnee Spector) and M.H.; writing—original draft preparation, A.M., S.S. (Samantha Schlaud), S.S. (Sydnee Spector) and M.H.; writing—review and editing, A.M., S.S. (Samantha Schlaud), S.S. (Sydnee Spector) and M.H.; visualization, A.M. and M.H.; supervision, A.M. and M.H.; project administration, A.M. and M.H.; funding acquisition, A.M. and M.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors thank the Clinical Outcomes Research and Education at Roseman University of Health Sciences College of Dental Medicine for the support of this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Parker, E.J.; Jamieson, L.M. Associations between indigenous Australian oral health literacy and self-reported oral health outcomes. *BMC Oral Health* **2010**, *10*, 3. [CrossRef] [PubMed]
2. Jin, L.J.; Lamster, I.B.; Greenspan, J.S.; Pitts, N.B.; Scully, C.; Warnakulasuriya, S. Global burden of oral diseases: Emerging concepts, management and interplay with systemic health. *Oral Dis.* **2016**, *22*, 609–619. [CrossRef] [PubMed]
3. Petersen, P.E. The World Oral Health Report 2003: Continuous improvement of oral health in the 21st century--the approach of the WHO Global Oral Health Programme. *Community Dent. Oral Epidemiol.* **2003**, *31*, 3–23. [CrossRef] [PubMed]
4. Shah, A.; Peacock, R.; Eliyas, S. Pulp therapy and root canal treatment techniques in immature permanent teeth: An update. *Br. Dent. J.* **2022**, *232*, 524–530. [CrossRef]
5. Ballikaya, E.; Koc, N.; Avcu, N.; Cavit Cehreli, Z. The quality of root canal treatment and periapical status of permanent teeth in Turkish children and teens: A retrospective CBCT study. *Oral Radiol.* **2022**, *38*, 405–415. [CrossRef]
6. Santipipat, C.; Kaewkamnerdpong, I.; Limpuangthip, N. Facilitating dental disease screening program in prisoners using an intraoral camera in teledentistry. *BDJ Open* **2023**, *9*, 18. [CrossRef]
7. Kassis, C.; Mehanna, C.; Khoury, P.; Tohme, H.; Cuevas-Suárez, C.E.; Bourgi, R.; Lukomska-Szymanska, M.; Hardan, L. Triple scan evaluation of internal and marginal adaptation of overlays using different restorative materials. *J. Esthet. Restor. Dent.* **2023**, *35*, 493–500. [CrossRef]
8. Stănuşi, A.; Iacov-Crăiţoiu, M.M.; Scrieciu, M.; Mitruţ, I.; Firulescu, B.C.; Boţilă, M.R.; Vlăduţu, D.E.; Stănuşi, A.Ş.; Mercuţ, V.; Osiac, E. Morphological and Optical Coherence Tomography Aspects of Non-Carious Cervical Lesions. *J. Pers. Med.* **2023**, *13*, 772. [CrossRef]
9. Kaplan, A.T.; Yalcin, S.O.; Sager, S.G.; Türkyılmaz, A.; İnan, R. Evaluation of optical coherence tomography findings and visual evoked potentials in Charcot-Marie-Tooth disease. *Int. Ophthalmo.* **2023**, *43*, 333–341. [CrossRef]
10. Rajpurkar, P.; Chen, E.; Banerjee, O.; Topol, E.J. AI in health and medicine. *Nat. Med.* **2022**, *28*, 31–38. [CrossRef]
11. Servicenow. What Is Machine Learning? Available online: https://www.servicenow.com/now-platform/what-is-machine-learning.html (accessed on 9 January 2024).
12. Erickson, B.J.; Korfiatis, P.; Akkus, Z.; Kline, T.L. Machine Learning for Medical Imaging. *Radiographics* **2017**, *37*, 505–515. [CrossRef] [PubMed]
13. Agrawal, P.; Nikhade, P. Artificial Intelligence in Dentistry: Past, Present, and Future. *Cureus* **2022**, *14*, e27405. [CrossRef] [PubMed]
14. Reyes, L.T.; Knorst, J.K.; Ortiz, F.R.; Ardenghi, T.M. Scope and challenges of machine learning-based diagnosis and prognosis in clinical dentistry: A literature review. *J. Clin. Transl. Res.* **2021**, *7*, 523–539. [PubMed]
15. Park, Y.-H.; Kim, S.-H.; Choi, Y.-Y. Prediction Models of Early Childhood Caries Based on Machine Learning Algorithms. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8613. [CrossRef]
16. Qu, X.; Zhang, C.; Houser, S.H.; Zhang, J.; Zou, J.; Zhang, W.; Zhang, Q. Prediction model for early childhood caries risk based on behavioral determinants using a machine learning algorithm. *Comput. Methods Programs Biomed.* **2022**, *227*, 107221. [CrossRef]
17. Ramos-Gomez, F.; Marcus, M.; Maida, C.A.; Wang, Y.; Kinsler, J.J.; Xiong, D.; Lee, S.Y.; Hays, R.D.; Shen, J.; Crall, J.J.; et al. Using a Machine Learning Algorithm to Predict the Likelihood of Presence of Dental Caries among Children Aged 2 to 7. *Dent. J.* **2021**, *9*, 141. [CrossRef]
18. Hung, M.; Voss, M.W.; Rosales, M.N.; Li, W.; Su, W.; Xu, J.; Bounsanga, J.; Ruiz-Negrón, B.; Lauren, E.; Licari, F.W. Application of machine learning for diagnostic prediction of root caries. *Gerodontology* **2019**, *36*, 395–404. [CrossRef]

19. Bichu, Y.M.; Hansa, I.; Bichu, A.Y.; Premjani, P.; Flores-Mir, C.; Vaid, N.R. Applications of artificial intelligence and machine learning in orthodontics: A scoping review. *Prog. Orthod.* **2021**, *22*, 18. [CrossRef]
20. Ariji, Y.; Yanashita, Y.; Kutsuna, S.; Muramatsu, C.; Fukuda, M.; Kise, Y.; Nozawa, M.; Kuwada, C.; Fujita, H.; Katsumata, A.; et al. Automatic detection and classification of radiolucent lesions in the mandible on panoramic radiographs using a deep learning object detection technique. *Oral Surg. Oral Med. Oral Pathol. Oral Radiol.* **2019**, *128*, 424–430. [CrossRef]
21. Bashirian, S.; Shirahmadi, S.; Seyedzadeh-Sabounchi, S.; Soltanian, A.R.; Karimi-Shahanjarini, A.; Vahdatinia, F. Association of caries experience and dental plaque with sociodemographic characteristics in elementary school-aged children: A cross-sectional study. *BMC Oral Health* **2018**, *18*, 7. [CrossRef]
22. Kuwada, C.; Ariji, Y.; Fukuda, M.; Kise, Y.; Fujita, H.; Katsumata, A.; Ariji, E. Deep learning systems for detecting and classifying the presence of impacted supernumerary teeth in the maxillary incisor region on panoramic radiographs. *Oral Surg. Oral Med. Oral Pathol. Oral Radiol.* **2020**, *130*, 464–469. [CrossRef] [PubMed]
23. Kılıc, M.C.; Bayrakdar, I.S.; Çelik, Ö.; Bilgir, E.; Orhan, K.; Aydın, O.B.; Kaplan, F.A.; Sağlam, H.; Odabaş, A.; Aslan, A.F.; et al. Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs. *Dentomaxillofac. Radiol.* **2021**, *50*, 20200172. [CrossRef] [PubMed]
24. Bouchahma, M.; Hammouda, S.B.; Kouki, S.; Alshemaili, M.; Samara, K. An Automatic Dental Decay Treatment Prediction using a Deep Convolutional Neural Network on X-Ray Images. In Proceedings of the 2019 IEEE/ACS 16th International Conference on Computer Systems and Applications (AICCSA), Abu Dhabi, United Arab Emirates, 3–7 November 2019.
25. Saghiri, M.A.; Garcia-Godoy, F.; Gutmann, J.L.; Lotfi, M.; Asgar, K. The reliability of artificial neural network in locating minor apical foramen: A cadaver study. *J. Endod.* **2012**, *38*, 1130–1134. [CrossRef] [PubMed]
26. Arısu, H.D.; Dalkilic, E.E.; Alkan, F.; Erol, S.; Uctasli, M.B.; Cebi, A. Use of Artificial Neural Network in Determination of Shade, Light Curing Unit, and Composite Parameters' Effect on Bottom/Top Vickers Hardness Ratio of Composites. *Biomed. Res. Int.* **2018**, *2018*, 4856707. [CrossRef]
27. World Health Organization. Early Child Development: A Powerful Equalizer. Available online: https://www.who.int/publications/i/item/early-child-development-a-powerful-equalizer-final-report-for-the-world-health-organization-s-commission-on-the-social-determinants-of-health (accessed on 17 November 2024).
28. ADA Division of Communications. Tooth eruption. *JADA* **2006**, *137*, 127.
29. Tricco, A.C.; Lillie, E.; Zarin, W.; O'Brien, K.K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M.D.J.; Horsley, T.; Weeks, L.; et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann. Intern. Med.* **2018**, *169*, 467–473. [CrossRef]
30. World Health Organization. Definition of Key Terms. Available online: https://www.who.int/hiv/pub/guidelines/arv2013/intro/keyterms/en/ (accessed on 19 October 2023).
31. HAMADEH, N.; ROMPAEY, C.V.; METREAU, E.; Eapen, S.G. New World Bank Country Classifications by Income Level: 2022–2023. Available online: https://blogs.worldbank.org/en/opendata/new-world-bank-country-classifications-income-level-2022-2023?utm_source=link_newsv9&utm_campaign=item_505373&utm_medium=copy (accessed on 19 October 2023).
32. Grier, A.; Myers, J.A.; O'Connor, T.G.; Quivey, R.G.; Gill, S.R.; Kopycka-Kedzierawski, D.T. Oral Microbiota Composition Predicts Early Childhood Caries Onset. *J. Dent. Res.* **2021**, *100*, 599–607. [CrossRef]
33. Al Kheraif, A.A.; Alshahrani, O.A.; Al Esawy, M.S.S.; Fouad, H. Evolutionary and Ruzzo–Tompa optimized regulatory feedback neural network based evaluating tooth decay and acid erosion from 5 years old children. *Meas. J. Int. Meas. Confed.* **2019**, *141*, 345–355. [CrossRef]
34. Nowak, A.J.; Dooley, D.; Mitchell-Royston, L.; Rust, S.; Hoffman, J.; Chen, D.; Menyman, B.; Wright, R.; Casamassimo, P.S. A Predictive Model for Primary Care Providers to Identify Children at Greatest Risk for Early Childhood Caries. *Pediatr. Dent.* **2020**, *42*, 450–456.
35. Woodsend, B.; Koufoudaki, E.; Lin, P.; McIntyre, G.; El-Angbawi, A.; Aziz, A.; Shaw, W.; Semb, G.; Reesu, G.V.; Mossey, P.A. Development of intra-oral automated landmark recognition (ALR) for dental and occlusal outcome measurements. *Eur. J. Orthod.* **2022**, *44*, 43–50. [CrossRef]
36. Saxena, D.; Caufield, P.W.; Li, Y.; Brown, S.; Song, J.; Norman, R. Genetic classification of severe early childhood caries by use of subtracted DNA fragments from Streptococcus mutans. *J. Clin. Microbiol.* **2008**, *46*, 2868–2873. [CrossRef] [PubMed]
37. Karhade, D.S.; Roach, J.; Shrestha, P.; Simancas-Pallares, M.A.; Ginnis, J.; Burk, Z.J.S.; Ribeiro, A.A.; Cho, H.; Wu, D.; Divaris, K. An Automated Machine Learning Classifier for Early Childhood Caries. *Pediatr. Dent.* **2021**, *43*, 191–197. [PubMed]
38. Ganiatsou, E.; Georgiadou, A.; Souleles, A.; Aidonis, A.; Protopsalti, T.; Tzevreni, S.; Konstantinidou, K.; Vasileiadou, S.; Siegmund, F.; Papageorgopoulou, C. Application of machine learning on isotopic data from tooth microsections for reconstructing weaning patterns and physiological stress. *J. Archaeol. Sci. Rep.* **2023**, *47*, 103765. [CrossRef]
39. Peng, J.; Zeng, X.; Townsend, J.; Liu, G.; Huang, Y.; Lin, S. A Machine Learning Approach to Uncovering Hidden Utilization Patterns of Early Childhood Dental Care Among Medicaid-Insured Children. *Front. Public Health* **2020**, *8*, 599187. [CrossRef]
40. Xiao, J.; Luo, J.; Mapes, O.L.; Wu, T.T.; Dye, T.; Jallad, N.A.; Hao, P.; Ruan, J.; Bullock, S.; Fiscella, K. Assessing a smartphone app (aicaries) that uses artificial intelligence to detect dental caries in children and provides interactive oral health education: Protocol for a design and usability testing study. *JMIR Res. Protoc.* **2021**, *10*. [CrossRef]
41. Xie, J.; Cho, H.; Lin, B.M.; Pillai, M.; Heimisdottir, L.H.; Bandyopadhyay, D.; Zou, F.; Roach, J.; Divaris, K.; Wu, D. Improved Metabolite Prediction Using Microbiome Data-Based Elastic Net Models. *Front. Cell. Infect. Microbiol.* **2021**, *11*, e32921. [CrossRef]

42. Liu, J.; Liu, Y.; Li, S.; Ying, S.; Zheng, L.; Zhao, Z. Artificial intelligence-aided detection of ectopic eruption of maxillary first molars based on panoramic radiographs. *J. Dent.* **2022**, *125*, 104239. [CrossRef]
43. Zaorska, K.; Szczapa, T.; Borysewicz-Lewicka, M.; Nowicki, M.; Gerreth, K. Prediction of Early Childhood Caries Based on Single Nucleotide Polymorphisms Using Neural Networks. *Genes* **2021**, *12*, 462. [CrossRef]
44. Heimisdottir, L.H.; Lin, B.M.; Cho, H.; Orlenko, A.; Ribeiro, A.A.; Simon-Soro, A.; Roach, J.; Shungin, D.; Ginnis, J.; Simancas-Pallares, M.A.; et al. Metabolomics Insights in Early Childhood Caries. *J. Dent. Res.* **2021**, *100*, 615–622. [CrossRef]
45. Koopaie, M.; Salamati, M.; Montazeri, R.; Davoudi, M.; Kolahdooz, S. Salivary cystatin S levels in children with early childhood caries in comparison with caries-free children; statistical analysis and machine learning. *BMC Oral Health* **2021**, *21*, 650. [CrossRef]
46. Quivey, R.G.; O'Connor, T.G.; Gill, S.R.; Kopycka-Kedzierawski, D.T. Prediction of early childhood caries onset and oral microbiota. *Mol. Oral Microbiol.* **2021**, *36*, 255–257. [CrossRef] [PubMed]
47. Raksakmanut, R.; Thanyasrisung, P.; Sritangsirikul, S.; Kitsahawong, K.; Seminario, A.L.; Pitiphat, W.; Matangkasombut, O. Prediction of Future Caries in 1-Year-Old Children via the Salivary Microbiome. *J. Dent. Res.* **2023**, *102*, 626–635. [CrossRef] [PubMed]
48. Montenegro, R.D.; Oliveira, A.L.I.; Cabral, G.G.; Katz, C.R.T.; Rosenblatt, A. A comparative study of machine learning techniques for caries prediction. In Proceedings of the International Conference on Tools with Artificial Intelligence, ICTAI, Dayton, OH, USA, 3–5 November 2008; pp. 477–481.
49. Ichimura, S. Migaco: Supporting young children's tooth brushing with machine learning. In *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*; Springer: Cham, Switherland, 2018; Volume 11000, pp. 173–184. [CrossRef]
50. Li, S.; Huang, S.; Guo, Y.; Zhang, Y.; Zhang, L.; Li, F.; Tan, K.; Lu, J.; Chen, Z.; Guo, Q.; et al. Geographic Variation Did Not Affect the Predictive Power of Salivary Microbiota for Caries in Children With Mixed Dentition. *Front. Cell. Infect. Microbiol.* **2021**, *11*, 680288. [CrossRef] [PubMed]
51. Wu, T.T.; Xiao, J.; Manning, S.; Saraithong, P.; Pattanaporn, K.; Paster, B.J.; Chen, T.; Vasani, S.; Gilbert, C.; Zeng, Y.; et al. Multimodal Data Integration Reveals Mode of Delivery and Snack Consumption Outrank Salivary Microbiome in Association With Caries Outcome in Thai Children. *Front. Cell. Infect. Microbiol.* **2022**, *12*, 881899. [CrossRef]
52. Hart, T.C.; Corby, P.M.; Hauskrecht, M.; Ok Hee, R.; Pelikan, R.; Valko, M.; Oliveira, M.B.; Hoehn, G.T.; Bretz, W.A. Identification of Microbial and Proteomic Biomarkers in Early Childhood Caries. *Int. J. Dent.* **2011**, *2011*, 196721. [CrossRef]
53. de Jesus, V.C.; Khan, M.W.; Mittermuller, B.A.; Duan, K.; Hu, P.; Schroth, R.J.; Chelikani, P. Characterization of Supragingival Plaque and Oral Swab Microbiomes in Children With Severe Early Childhood Caries. *Front. Microbiol.* **2021**, *12*, 683685. [CrossRef]
54. de Jesus, V.C.; Shikder, R.; Oryniak, D.; Mann, K.; Alamri, A.; Mittermuller, B.; Duan, K.; Hu, P.; Schroth, R.J.; Chelikani, P. Sex-Based Diverse Plaque Microbiota in Children with Severe Caries. *J. Dent. Res.* **2020**, *99*, 703–712. [CrossRef]
55. You, W.Z.; Hao, A.M.; Li, S.; Wang, Y.; Xia, B. Deep learning-based dental plaque detection on primary teeth: A comparison with clinical assessments. *Bmc Oral Health* **2020**, *20*, 141. [CrossRef]
56. Tamaki, Y.; Nomura, Y.; Katsumura, S.; Okada, A.; Yamada, H.; Tsuge, S.; Kadoma, Y.; Hanada, N. Construction of a dental caries prediction model by data mining. *J. Oral Sci.* **2009**, *51*, 61–68. [CrossRef]
57. Yan, Z.; Chen, Y.; Wang, X.; Zhu, J.; Li, J. Recognition and classification of children's molars based on deep learning. *J. Intell. Fuzzy Syst.* **2022**, *43*, 1271–1283. [CrossRef]
58. Rubagumya, F.; Hopman, W.M.; Gyawali, B.; Mukherji, D.; Hammad, N.; Pramesh, C.S.; Zubaryev, M.; Eniu, A.; Tsunoda, A.T.; Kutluk, T.; et al. Participation of Lower and Upper Middle-Income Countries in Clinical Trials Led by High-Income Countries. *JAMA Netw. Open* **2022**, *5*, e2227252. [CrossRef] [PubMed]
59. Sharma, S.; Verhagen, A.P.; Elkins, M.; Brismée, J.-M.; Fulk, G.D.; Taradaj, J.; Steen, L.; Jette, A.; Moore, A.; Stewart, A.; et al. Research from low-income and middle-income countries will benefit global health and the physiotherapy profession, but it requires support. *J. Man. Manip. Ther.* **2023**, *31*, 305–310. [CrossRef] [PubMed]
60. Asiri, F.Y.; Kruger, E.; Tennant, M. Global Dental Publications in PubMed Databases between 2009 and 2019-A Bibliometric Analysis. *Molecules* **2020**, *25*, 4747. [CrossRef] [PubMed]
61. Nguyen, T.T.; Larrivée, N.; Lee, A.; Bilaniuk, O.; Durand, R. Use of Artificial Intelligence in Dentistry: Current Clinical Trends and Research Advances. *J. Can. Dent. Assoc.* **2021**, *87*, 1488–2159. [CrossRef]
62. American Dental Association. Dental Radiographs: Benefits and Safety. Available online: https://www.ada.org/-/media/project/ada-organization/ada/ada-org/files/resources/research/for_the_dental_patient_sept_2011.pdf (accessed on 18 November 2023).

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