IJKG INTERDENTAL Jurnal Kedokteran Gigi

Interdental Jurnal Kedokteran Gigi
Website: https://e-journal.unmas.ac.id/index.php/interdental
ISSN 1979-9144 (print), ISSN 2685-5208 (online)

Systematic Review

Mapping The Use of AI Interventions in Childhood Caries Prevention Based on Leavell and Clark's Levels: A Scoping Review

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Received date: May 6, 2026 **Accepted date: June 26, 2026** **Published date: August 12, 2026**

KEYWORDS

Artificial intelligence, caries, children, prevention

DOI: 10.46862/interdental.v22i2.14043

ABSTRACT

Introduction: The high burden of childhood dental caries highlights the need for innovative approaches. Artificial Intelligence (AI) offers a breakthrough in enabling more efficient, measurable efforts to prevent and detect dental caries. Therefore, this scoping review aims to map the existing evidence on the use of AI interventions in the prevention of childhood dental caries based on Leavell and Clark's prevention model. **Review**: This scoping review analyzed 49 studies from various countries that examined the application of AI in childhood caries prevention, using the Leavell and Clark framework. At the health promotion level, behavior-based chatbot applications were shown to significantly improve caregivers' knowledge and toothbrushing habits. In the specific protection setting, predictive models based on tabular data and the salivary microbiome identified high-risk children before lesions formed, with AUC values ranging from 0.77 to 0.94. For early detection, deep learning algorithms trained on radiographic images and intraoral photographs demonstrated high accuracy in detecting caries lesions, including incipient lesions, with a sensitivity of up to 94.7%. For disability prevention, AI models successfully predicted the success of caries arrest therapy with silver diamine fluoride. The main limitations identified were a small sample size, a lack of cross-population external validation, and gaps in model interpretability at the clinical level. **Conclusion**: The use of AI interventions for childhood dental caries is unevenly distributed across Leavell and Clark's five preventive levels, especially for specific protection.

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How to cite this article: Anugrah PM, Olivia M, Adiatman M, Darwita RR. Mapping The Use of Ai Interventions in Childhood Caries Prevention Based On Leavell And Clark's Levels: A Scoping Review. Interdental Jurnal Kedokteran Gigi. 2026;22(2):353-63. doi: 10.46862/interdental.v22i2.14043

INTRODUCTION

Dental caries remains prevalent in children globally. The 2021 Global Burden of Disease Study reported that 520 million children have caries in their deciduous teeth.[1] Qin et al. examined GBD data from 1990 to 2019 and found that untreated caries in primary teeth increased by 11.74%, resulting 1.15 billion new cases.[2] Additionally, a meta-analysis reviewed data from 100 publications across 49 countries and estimated the worldwide prevalence of Early Childhood Caries (ECC) at 49%. Disparities exist between regions, varying from 34% in Latin America to 72% in the Middle East, and between high-income (30%) and low-income countries (57%).[3] The World Health Organization estimated that 60–90% of children under 12 have caries in various countries.[1]

The progression of untreated caries results in a series of consequences that extend beyond destruction of the tooth surface. Children affected by caries frequently experience prolonged pain, impaired chewing function, decreased nutritional intake, impaired sleep quality, and repeated absences from school, as reported by Astuti et al.[4] In advanced stages, decay can extend to the pulp and periapical tissues, leading to abscesses, cellulitis, or orofacial infections, while premature loss of primary teeth also threatens the integrity of the dental arch and leads to malocclusion.[5] Recognition of the significant burden associated with dental caries led the World Health Assembly in 2021 to adopt a resolution on oral health, which was further developed in the WHO Global Oral Health Action Plan, aiming to reduce the prevalence of oral disease by 10% by 2030.[1]

This challenge makes childhood caries a priority on the global health agenda. Effective caries control requires a comprehensive and structured framework rather than isolated interventions. Leavell and Clark's framework is an effective strategy that was first introduced in 1953 and revised in 1965.[6,7] These describe five levels of prevention and focus on different disease stages. These five levels are commonly grouped into three major phases of prevention: primary, secondary, and tertiary. Primary prevention consists of health promotion and specific protection.[7] Health promotion could increase children's willingness to engage in daily tooth brushing through education, consumption of cariogenic foods, and visiting the dentist regularly.[8] Meanwhile, specific protection against specific causative agents.[9] Secondary prevention focuses on early diagnosis and prompt treatment to detect lesions at the earliest stage and halt disease progression.[10] Tertiary prevention encompasses disability limitation to reduce further harm and prevent complications, along with rehabilitation aimed at restoring lost function.[9] These categories are still important in epidemiology and preventive medicine.

The Leavell and Clark framework applies directly to every level of pediatric dentistry. Health promotion is realized through dental and oral health education for parents and children, low-cariogenic diet counselling, and toothbrushing promotions in school settings.[11] Specific protections include topical fluoride application, systemic fluoride administration in eligible populations, and fissure sealant placement on deep fissures of children's molars to prevent plaque accumulation.[12] Early diagnosis and prompt treatment include routine examinations, caries screening using the International Caries Detection and Assessment System (ICDAS), and minimally invasive restorative procedures on early-detected lesions.[13] Disability limitation refers to restorative fillings and pulp treatment to prevent further decay and maintain primary teeth in the dental arch.[14]

Rehabilitation is achieved through the installation of space maintainers, stainless steel crowns, or removable dentures for children who experience premature loss of primary teeth to maintain chewing function, aesthetics, and jaw growth.[15] The hierarchical structure maintains the relevance of the Leavell and Clark framework as an analytical tool for developing comprehensive strategies to prevent childhood dental caries.

With the advancement of digital technology, dental practice is changing, characterized by the integration of machine learning and artificial neural network systems. Researchers have tested algorithms such as convolutional neural networks, deep learning, and machine learning on various dental imaging modalities, including periapical radiographs, bitewings, panoramic radiographs, and standard intraoral photos. Lee et al.[16] achieved 88.0–89.0% accuracy using the GoogleNet Inception v3 architecture on periapical radiographs.[16] In comparison, Şevik et al.[17] identified YOLOv11x as the most effective among four YOLO variants for pediatric panoramic radiographs, reporting an mAP50 of 0.91.[17] This innovation has led to the development of smartphone-based applications such as AICaries, which allow parents to independently scan their children for potential lesions at home.[18] These tools may increase access to dental services in communities with limited pediatric dentistry. In addition, predictive models using Multilayer Perceptron, Random Forest, and Support Vector Machine algorithms reported 97.4% accuracy in risk prediction among 780 Turkish children.[19] Similarly, an artificial neural network model utilizing single nucleotide polymorphisms in the AMELX, TUFT1, MMP16, and ENAM genes achieved 90.9–98.4% accuracy.[20] These results suggest that intelligent computing technologies are advancing beyond traditional diagnostic roles and are increasingly being applied to preventive strategies.

Although extensive literature exists on the application of AI interventions in childhood dental caries prevention, most reviews focus on algorithm performance in detecting childhood dental caries. The role of AI interventions in childhood dental caries for health promotion, special protection, and rehabilitation has not been synthesized within a comprehensive framework.[21] The breadth and heterogeneity of the literature within the Leavell and Clark framework limit the suitability of systematic reviews with narrowly focused questions. Additionally, an initial search of PubMed, the Cochrane Database of Systematic Reviews, PROSPERO, and the Open Science Framework revealed no scoping or systematic reviews that specifically map the use of intelligent computing technology across the levels of childhood caries prevention as defined by Leavell and Clark. Therefore, this review aims to map the existing evidence on the use of AI interventions in the prevention of childhood dental caries based on Leavell and Clark's prevention model.

REVIEW

This review followed the guidelines of JBI Methodology for scoping review.[22] Reporting of this review follows the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines.[23] This review has been registered in Open Science Framework (OSF) (https://osf.io/6cmrj).

The inclusion and exclusion criteria refer to the PCC framework that has been compiled. Participants refer to children aged 6 months–12 years. The concept elemen refers to the use of intelligent computing technology such as machine learning, deep learning, convolutional neural networks, and smartphone-based applications in caries prevention based on Leavell and Clarks's, while the context covers all settings including clinics, dental and oral hospitals, health centers, school dental health businesses, and household environments that utilize smartphone-based applications. A summary of the PCC is presented in Table 1.

Table 1. The inclusion and exclusion criteria.

	Inclusion	Exclusion
Population	Children refer to infants, toddlers, school-aged children, adolescents (usually up to 12 years of age) who still have primary teeth or in mixed dentation phase with dental cavity, high risk of caries, or health teeth in the context of a prevention program.	Participants aged >12 years, such as teenagers, adults, and the elderly are the main participants and children are only mentioned marginally without being the focus of the analysis.
Concept	The use of machine learning, deep learning, CNNs, SVMs and applications based on intelligent algorithms in the prevention of dental caries, including risk prediction, screening, early detection, diagnosis, recommendations for intervention, health education, monitoring, or clinical decision support.	Digital technology without intelligent algorithms; oral diseases other than caries. AI is merely described as a statistical analysis method, and no predictive models are reported. The article explores the association between risk factors and dental caries and uses an ANN to identify the variables with the greatest influence.
Context	Can be mapped to one of the Leavell-Clark levels; covers clinical and home settings.	
Type of Sources	Primary studies (RCT, cohort, cross-sectional, case-control, qualitative, case study, mixed-methods) Full text Grey literature (thesis, book, internet website)	Conference abstracts without peer reviews Editorials Opinion pieces Letters to the editor Commentaries without research data
	English language No limited year of publications	Other language

The search strategy followed the JBI methodology for scoping reviews. First, an initial search was conducted in Medline (Ovid) to identify key keywords and index terms from the titles, abstracts, subject headings, and author-supplied keywords of included articles. Second, a comprehensive search using refined keywords was conducted across Embase (Ovid), PubMed, and Scopus. Details of search strategies are presented in Supplementary 1.

Articles across databases were exported into Covidence (Veritas Health Innovation, Melbourne, Australia), a web-based tool that speeds up the review scoping process and helps identify duplicates. After the duplicate document was removed, two reviewers (PMA & MO) conducted blinded screening independently in two steps. The first step involved screening titles and abstracts. Pilot testing was conducted on the first 30 articles to ensure inter-rater reliability, with a minimum agreement threshold of 80% before proceeding. The second step continued with the full manuscript review. If there are disagreements between two researchers, this discussion or the involvement of a third reviewer (MA) is required. Reasons for exclusion from all steps were recorded in detail and reported in the PRISMA-ScR flowchart.

Data extraction was performed using a charting sheet prepared by the researchers themselves, following JBI recommendations. The extracted data were organized into the following categories: (1) Characteristics study, including author, year of publication, country of origin, and study design; (2) Participant characteristics, including age range, number of subjects, type of teeth observed, and service setting; (3) AI characteristics, including name of AI, algorithm type, input data modality, and purpose of AI; (4) Prevention levels, classified based on the Leavell and Clark framework as health promotion, specific protection, early diagnosis and prompt treatment, disability limitation, and rehabilitation; (5) Reported Outcome; and (6) Barriers and facilitators of AI technology implementation. Authors of the articles will be contacted for unclear or missing data, with a two-week response period; all efforts and responses will be documented. Disagreements between the two researchers will be resolved by a third reviewer.

The extracted data were analyzed using quantitative-descriptive and qualitative-thematic approaches. The quantitative-descriptive approach examined the distribution of articles by year of publication, country of implementation, study design, type of intelligent computing technology, input data modality, and Leavell and Clark's levels of prevention. Meanwhile, the qualitative-thematic approach involved grouping the findings into the five levels of prevention outlined by Leavell and Clark, which served as the primary reference for thematic mapping. The results of the study are presented in tables, visual charts, and descriptive narratives.

A literature search was conducted across four databases, including Medline via Ovid, Scopus, Embase via Ovid, and PubMed, yielding a total of 531 initial records (79, 195, 106, and 151, respectively). Following deduplication, 255 duplicate records were removed, leaving 261 records for the title and abstract screening stage. At this stage, 192 records were excluded as irrelevant to the review topic, and attempts were made to download the full texts of 69 reports. One report was inaccessible, leaving 68 reports to proceed to the eligibility assessment. During the eligibility assessment, 20 reports were excluded: 15 due to the wrong population, 3 due to the wrong intervention, and 2 due to the wrong source type. Ultimately, 49 studies met all inclusion criteria and were included in this scoping review, with each study represented by a single report (n=49). Details are presented in Figure 1.

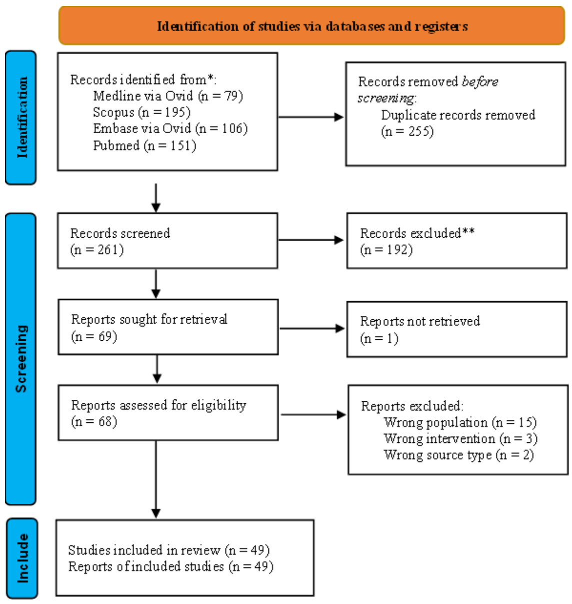

Figure 1. PRISMA ScR 2020 Flow Diagram

This review included 49 studies aligning the inclusion criteria. Mapped into the four main categories of AI architecture, including Machine Learning (ML), including shallow neural networks, Convolutional Neural Networks (CNNs), Transformers, as well as Large Language Models (LLMs) and rule-based chatbots. Classical ML dominates with 29 studies (59.2%), followed by CNNs with 13 studies (26.5%), LLMs/chatbots with 5 studies (10.2%), and Transformers with 2 studies (4.1%). The most frequently used algorithms within the ML group were random forests, logistic regression, XGBoost, support vector machines, and multilayer perceptron. The majority were applied to tabular data from socio-demographic behavior questionnaires, saliva biomarkers, microbiome profiles, or electronic health records.

The distribution of the 49 studies reviewed shows a sharp upward trend, with a peak in publications in 2025 (16 studies), following an initial wave in 2021 (n=9). Machine Learning consistently dominated throughout the observation period, whilst Convolutional Neural Networks only emerged from 2022 and grew steadily until 2026. Transformers were only recorded in 2024, and LLMs exploded in 2025 following the post-ChatGPT era. More than 75% of studies were published in the last three years, reflecting the post-pandemic acceleration in the adoption of Artificial Intelligence (AI) in childhood caries (Figure 2).

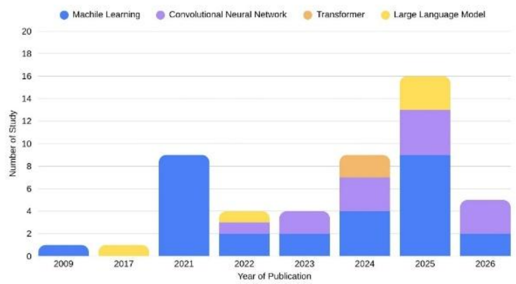

Figure 2. Distribution of publication years and types of AI algorithms

Geographically, the study came from 19 countries with the largest contributions from the United States (n=10), China (n=6), India (n=6), Thailand (n=4), and Australia (n=3); other countries include Poland, South Korea, Malaysia, the United Kingdom, Saudi Arabia (n=2), as well as Jordan, Japan, Indonesia, Brazil, Bangladesh, Iran, Egypt, Germany, and Portugal (n=1) (Figure 3).

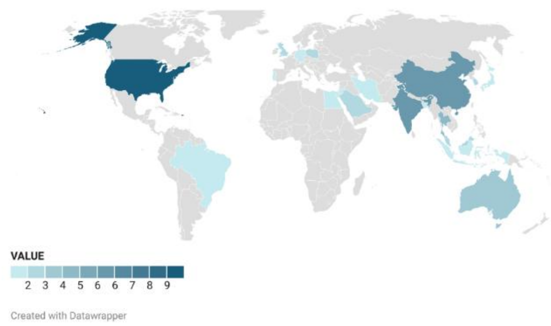

Figure 3. Geographical Distribution of The Countries of Study

Cross-sectional design dominated (n=23), followed by cohort/longitudinal (n=7), diagnostic accuracy (n=3), RCT (n=3), quasi-experimental (n=2), and the remaining studies were prospective, retrospective, observational, pilot, and algorithm development. The target population ranged from infants <1 year to 17-year-old adolescents, concentrated in the preschool (2–6 years) and early school age (6–12 years) groups. This age group is the critical period for Early Childhood Caries (ECC).

Based on the service setting, most studies were conducted in dental clinics/hospitals (n=30), at the community/population level (n=30), in schools (n=18), at home/telehealth (n=13), and in preschools (n=6). The input data modalities included demographic data and questionnaires (n=16), saliva/biomarkers (n=11), intraoral photographs (n=10), genetic data (n=10), electronic medical records (n=9), panoramic radiographs (n=4), 3D intraoral scans (n=1), and natural language inputs (n=4). Details are presented in Supplementary 2.

The study's mapping of the five levels of Leavell & Clark's prevention model served as the main analytical framework for this review. Distributions showed early diagnosis and prompt treatment level is the prevention category with the highest number of studies and the most diverse range of algorithms, encompassing classical machine learning (11 studies), convolutional neural networks (10 studies), transformers (2 studies), and large language models (1 study). In contrast, the specific protection level is dominated by machine learning (15 studies), whilst health promotion makes the most use of large language models and chatbots (5 studies). Additionally, the Disability Limitation level has only one Machine Learning-based study, and the Rehabilitation level is empty (Figure 4).

	Machine Learning	Convolutional Neural Network	Transformer	Large Language Model
Health Promotion	1	1	0	5
Spesific Protection	15	1	0	1
Early Diagnosis and Prompt Treatment	11	10	2	1
Disability Limitation	1	0	0	0
Rehabilitation	0	0	0	0

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Figure 4. Mapping Leavell & Clark's Five-Level Prevention Model Based on the AI Algorithm Type.

Seven studies used AI to support education and the development of oral health behaviors before disease onset.[24,25,26,27,28,29,30] Four chatbot/LLM-based studies: the "21-Day FunDee" chatbot for caregivers of children aged 6–36 months[27,28,29], the evaluation of GPT-3.5 as a source of parental education on ECC[25], and a hybrid deep-learning model of ECC prediction based on parental knowledge and attitudes[26]. Kang, et al.[24] used TensorFlow Lite for image classification to enable real-time toothbrushing motion recognition with augmented reality feedback[24], while Sinha & Deb (2017) tested an Intelligent Tutoring System for children aged 5–10 that used multimedia modules and toothbrushing games on 3D models via the Wii Remote interface.[30] Key findings showed significant improvements in knowledge, attitudes, self-efficacy, and frequency/duration of post-intervention toothbrushing with low implementation costs. The knowledge gaps are that long-term follow-up to clinical caries incidence is limited, linguistic-cultural adaptation has not been evenly distributed, and the clinical accuracy of generic LLM content has not been validated.

Seventeen studies focused on identifying high-risk children before the onset of caries lesions to enable specific protection (fluoride varnish, fissure sealant, dietary modification, prophylactic SDF, dental home).[31,32,33,34,35,36,37,38,39,40,41,42,43,44,20,45,46] Model inputs varied across studies, including behavioral-sociodemographic questionnaires[35,36,37,39,41,42,43,44], salivary microbiome[40,45], genetic markers/SNPs[20], and longitudinal clinical data[34,38]. Distinctively, Liu, et al.[33] developed a multitask automatic detection for the first permanent molar sealant fissure indication[33], and Matsuyama et al.[46] used causal machine learning to evaluate the effects of water fluoridation on 17,517 Australian children.[46] Random forests, XGBoost, logistic regression, and neural networks are often compared head-to-head, with AUCs of 0.70–0.90. A key feature is the preference for inexpensive, non-clinical data over extensive in-person exams, which is important where dental health workers are scarce. However, gaps remain in minimal cross-population external validation, reliance on potentially biased self-reports, and unclear pathways for integrating predictive outputs into primary service flows.

This level dominated this review (24 studies).[47,48,49,50,51,52,53,54,19,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69] Most research focused on the automatic detection of caries lesions in the pre-cavitation (incipient) stage. Four main approaches emerged: (1) deep learning-based image detection, using panoramic radiography[47,60,66], smartphone intraoral photographs[48,51,55,59,63,64], and 3D intraoral scanning[58]. These used CNN architectures (ResNet, EfficientNet, MobileNet) and a vision transformer (Swin Transformer), achieving sensitivity and accuracy of over 85%. However, precision was low due to high false positives in primary or mixed dentition.[47] (2) Questionnaire-tabular-based screening appeared in 6 studies.[50,53,19,57,61,69] This included a short-form, calibrated 10-item Item Response Theory tool.[61,69] (3) A multimodal biomarker approach integrated saliva, microbiome, and clinical data.[54,56,62,65,67] Hashim et al.[54] combined saliva parameters with Laser-Induced Breakdown Spectroscopy to classify four levels of ECC severity.[54] Koopaie et al.[67] used the salivary biomarkers cystatin S and ML for the detection of ECC.[67] (4) AI-based asynchronous teledentistry enabled school or home screening with remote dentist support.[48,51,55,59,68] This approach supported population assessments, such as California's KOHA.[55] AI reproduced clinician assessments with moderate-to-high kappa values and increased screening speed by 5–10 times. Limitations include variable smartphone image quality and the requirement for prospective validation.

Only one study was identified. The study developed a model to predict caries arrest on the tooth surface after treatment with 38% SDF or 25% $AgNO_3$ + 5% NaF. The study population was 880 pre-school children and 4,157 caries lesions and 30 months follow-up.[70] Six algorithms were evaluated to evaluate predictive performance (Naive Bayes, logistic regression, decision tree, random forest, SVM, XGBoost) with random forest and XGBoost performing best (0.74 accuracy; AUROC 0.86). Furthermore, SHAP analysis identified key predictors for personalizing therapy selection. This framework supports therapeutic decision-making and limits the progression of existing caries.[70]

None of the studies applied AI to post-treatment rehabilitation of childhood caries (e.g., monitoring long-term restoration success, predicting retreatment needs, or providing complex post-treatment functional and psychosocial rehabilitation support). This is the most significant gap in the current literature.

CONCLUSION

This scoping review shows that the use of AI interventions in the prevention of childhood dental caries has concentrated on early diagnosis and specific protection, while health promotion and disability limitation remain limited, and rehabilitation has not yet been implemented. These findings suggest the need for further, more balanced research across all levels of prevention in Leavell and Clark's model so that the potential of AI can be used comprehensively to reduce the burden of childhood dental caries.

ACKNOWLEDGMENT

This review was funded by the Directorate General of Higher Education, Ministry of Education, Culture, Research, and Technology, on the PMDSU research scheme with grant number PKS-578/UN2.RST/HKP.05.00/2025.

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