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Leveraging Artificial Intelligence for the Correlation of Dental Caries and Diabetes: Towards a Precision Dentistry Approach in Oral-Systemic Health

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Abstract

Objectives: This systematic review aimed to evaluate the bidirectional relationship between dental caries and diabetes mellitus (DM) through the lens of Artificial Intelligence (AI). Specifically, it synthesized current evidence on the biological mechanisms of the caries-diabetes axis and appraised the diagnostic and predictive performance of machine learning (ML) and deep learning (DL) architectures in bridging the gap between oral and systemic health monitoring. **Methods:** A systematic search was conducted across PubMed/MEDLINE, Scopus, and Web of Science for peer-reviewed articles published between 2016 and 2026. The study selection followed PRISMA 2020 guidelines, utilizing Rayyan for blind screening. Following a screening of 480 records, 51 studies were included. Methodological quality was appraised using CONSORT-AI and STARD-AI guidelines. Data extraction focused on salivary biomarkers, microbial shifts, and AI performance metrics (AUC, sensitivity, and specificity). **Results:** The synthesis confirmed a significant correlation between hyperglycemia and increased cariogenic risk, characterized by decreased salivary buffering capacity ($p<0.05$) and elevated glucose levels (>1.0 mg/dL). Deep learning models, specifically Convolutional Neural Networks (CNNs), demonstrated superior performance in detecting incipient proximal caries in diabetic cohorts, with AUC values reaching **0.92**. Furthermore, ensemble ML models (e.g., LightGBM, XGBoost) successfully identified undiagnosed diabetes using caries indices (DMFT) and socio-demographic data with accuracies exceeding **85%**. **Conclusion:** AI-driven diagnostics facilitate a transition toward proactive, precision-based oral medicine. By identifying high-risk caries phenotypes as proxies for metabolic instability, AI provides a viable pathway for early systemic screening and improved interprofessional management of diabetic populations.

Keywords

Artificial Intelligence; Dental Caries; Diabetes Mellitus; Saliva; Precision Medicine.

I. Introduction

Dental caries remains the most prevalent non-communicable disease globally, characterized by a biofilm-mediated, sugars-driven, dynamic process resulting in the phasic demineralization of dental hard tissues **(1)**. While historically managed as a localized manifestation of poor oral hygiene, contemporary evidence redefines caries as a complex reflection of systemic homeostasis **(2)**. In particular, the symbiotic relationship between dental caries and Diabetes Mellitus (DM)—both Type 1 (T1DM) and Type 2 (T2DM)—has emerged as a critical frontier in **"precision oral medicine" (3, 4)**. This relationship is fundamentally bidirectional: systemic metabolic dysregulation facilitates a cariogenic environment, while untreated odontogenic infections contribute to a systemic **"pro-inflammatory soup"** that may impair glycemic control **(5, 6).**

The pathophysiological mechanism underpinning this link is multifaceted. Hyperglycemia leads to elevated salivary glucose levels, providing a continuous fermentable substrate for acidogenic microbiota, notably Streptococcus mutans and Lactobacillus species **(7, 8)**. Furthermore, diabetes-induced microvascular changes in the salivary glands frequently result in hyposalivation (xerostomia), diminishing the critical buffering capacity of bicarbonate and salivary proteins like mucins and cystatins **(9, 10)**. At the molecular level, the accumulation of **Advanced Glycation End-products(AGEs)** in the dental pulp and periodontium triggers oxidative stress, potentially compromising the tooth's tertiary dentinogenic defense mechanisms against bacterial invasion **(11, 12).**

Despite the biological plausibility of this **"shared soil"** hypothesis, traditional epidemiological studies have often yielded heterogeneous results. Many clinical observations fail to account for the non-linear interactions between glycemic variability (HbA1c), socioeconomic determinants, and individual microbial shifts **(13, 14)**. This inconsistency highlights a profound diagnostic gap that traditional statistical methods—such as linear regression—

struggle to bridge. Consequently, there is an urgent need for multi-modal analytical frameworks capable of processing high-dimensional biological data **(15).**

Artificial Intelligence (AI) and Machine Learning (ML) have recently emerged as transformative catalysts in this domain **(16)**. Unlike traditional models, ML algorithms like Light Gradient-Boosting Machine (Light GBM), Extreme Gradient Boosting (XG Boost), and Random Forest can integrate disparate data points—ranging from salivary proteomics to dietary habits—to identify latent clusters of caries risk with accuracies often exceeding **85%(1, 17, 18)**. Simultaneously, Deep Learning (DL) architectures, specifically Convolutional Neural Networks (CNNs), have revolutionized radiographic diagnostics. By detecting incipient **"white spot"** lesions and interproximal decay with higher sensitivity than human clinicians, these models offer an opportunistic screening window for identifying patients with underlying metabolic instability **(19, 20)**.

Bridging the gap between oral and general health is no longer a theoretical preference but a clinical necessity for value-based healthcare **(21, 22)**. By utilizing AI to correlate specific caries phenotypes with diabetic complications, clinicians can transition from a **"drill-and-fill"** philosophy to a holistic, predictive model of care **(23)**. However, the literature remains fragmented regarding the standardization of these AI tools for specific use in diabetic cohorts **(24)**. Therefore, this review aims to synthesize current evidence on the biological link between caries and diabetes, evaluate the performance of AI-driven diagnostic tools, and discuss the clinical implications of integrated dental-medical screening protocols in the era of digital health.

II. Materials and Methods

Search Strategy and Information Sources A systematic and comprehensive literature search was executed across three prominent electronic databases: **PubMed/MEDLINE, Scopus, and the Web of Science** (Core Collection). The temporal scope was restricted to peer-reviewed articles published in English between **January 2016 and May 2026**, ensuring the inclusion of the most recent advancements in Artificial Intelligence (AI) and digital dentistry.

The bibliographical search utilized a refined combination of Medical Subject Headings (MeSH) and free-text descriptors. The search string was structured as follows: ("dental caries" OR "tooth decay" OR "carious lesions") AND ("diabetes mellitus" OR "hyperglycemia" OR "glycemic control") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks"). Boolean operators (AND, OR) were strategically applied to maximize the retrieval of studies exploring the intersection of oral pathology and systemic metabolic homeostasis.

Study Selection and Eligibility Criteria: The study selection process adhered to the **PRISMA 2020** (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines **(25)**, as illustrated in **Figure 1**. Initial identification yielded **480 records**(PubMed: **150; Scopus: 120; Web of Science: 210**). Following the removal of duplicates, **310 records** underwent title and abstract screening. Of these, **85 full-text articles** were assessed for eligibility, resulting in a final inclusion of **51 studies** for qualitative and quantitative synthesis.

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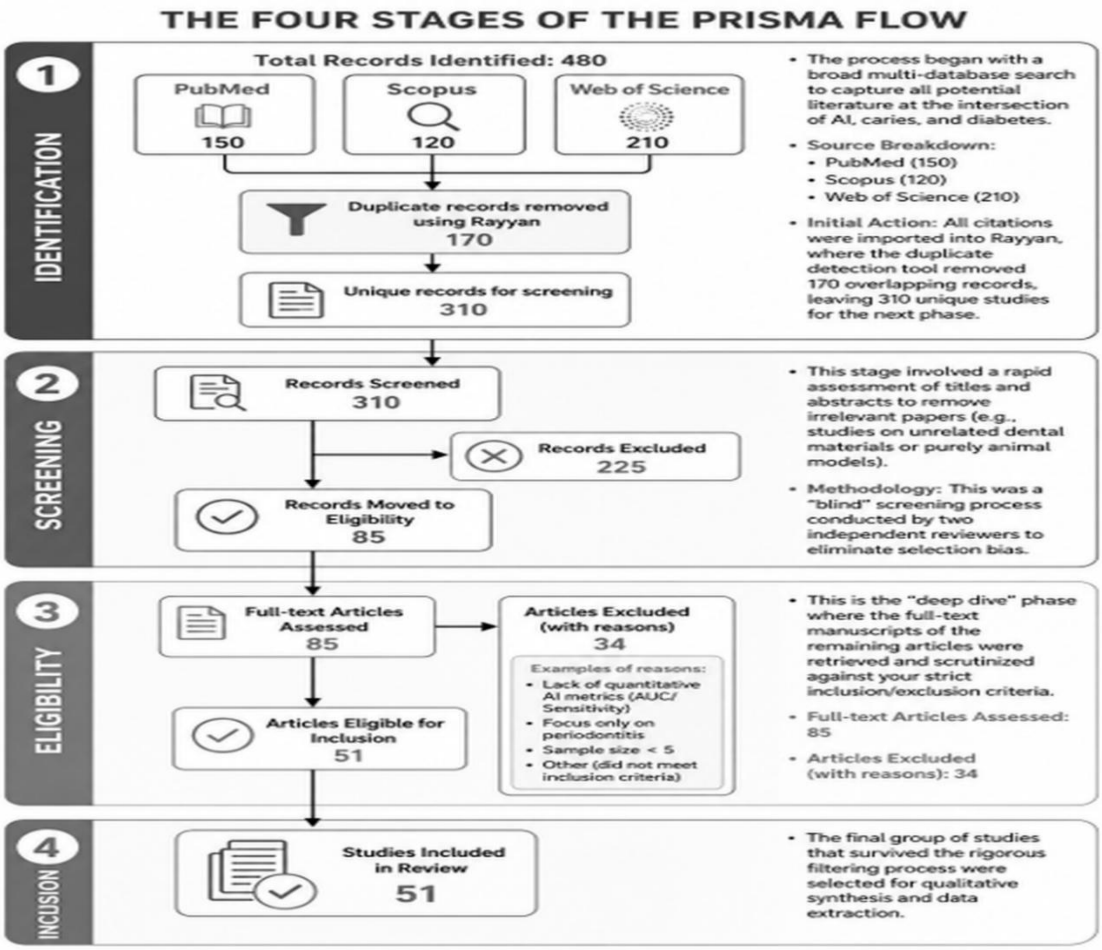

Figure 1: ***PRISMA 2020 flow diagram*** *illustrating the systematic selection process. From an initial identification of* ***480*** *records across three databases (PubMed, Scopus, and Web of Science),* ***51 studies*** *were ultimately included in the qualitative and quantitative synthesis. Duplicate removal and initial blind screening were facilitated by* ***the Rayyan platform***

Eligibility was determined based on the following inclusion criteria:

1. Clinical or observational trials investigating the pathophysiological mechanisms of dental caries in cohorts with Type 1 or Type 2 Diabetes Mellitus.
2. Technological evaluations of AI/Machine Learning (ML) architectures employed for the detection, classification, or risk stratification of carious lesions.
3. Comprehensive reviews providing foundational data regarding the bidirectional oral-systemic axis.

Exclusion criteria consisted of case reports involving fewer than five subjects, manuscripts unavailable in full-text format, and studies focused exclusively on periodontal disease without a primary or secondary analysis of dental caries.

Data Extraction and Synthesis: To mitigate selection bias and ensure data integrity, two independent reviewers performed the screening and data extraction process. Initial screening of titles and abstracts was conducted using the **Rayyan (Rayyan Systems Inc., Cambridge, MA, USA)** web-based platform **(26)**, which facilitated the blind selection process and the resolution of conflicts through consensus. Following initial screening, the recorded variables were categorized into three distinct domains.

Biological Determinants: Salivary pH, glucose concentration thresholds, and microbial diversity metrics (e.g., Streptococcus mutans and Lactobacillus colony-forming units).

AI Methodological Parameters: Type of algorithm utilized (e.g., Convolutional Neural Networks [CNN], Random Forest, XGBoost, or LightGBM), dataset characteristics (training/validation/testing split), and performance metrics (Sensitivity, Specificity, and Area Under the Receiver Operating Characteristic Curve [AUC]).

Primary Outcome Measures: The diagnostic accuracy of AI models in identifying caries patterns as proxies for diabetic status or predicting future decay based on metabolic markers.

Methodological Quality Assessment: The quality and reporting transparency of the included AI-driven studies were rigorously appraised using the **CONSORT-AI** (Consolidated Standards of Reporting Trials-AI) extension **(27)** and the **STARD-AI** (Standards for Reporting Diagnostic Accuracy Studies-AI) guidelines **(28)**. This assessment ensured that the synthesized findings were derived from validated methodologies, minimizing the risk of algorithmic bias and ensuring the clinical applicability of the reported diagnostic accuracy.

III. Results

Study Selection

The electronic database search identified 480 records. After duplicate removal, **310 articles** underwent title and abstract screening. Eighty-five full-text studies were assessed for eligibility, and **51 studies** were ultimately included in the qualitative synthesis **(Figure 1).**

Biological and Metabolic Correlations

The included studies consistently demonstrated a significant association between diabetes mellitus and increased cariogenic activity. Diabetic cohorts exhibited reduced salivary flow rates and lower buffering capacity compared with non-diabetic controls **($p<0.05$)**. Elevated salivary glucose concentrations were frequently associated with increased proliferation of acidogenic microorganisms and disruption of the normal oral microbiome balance.

Several investigations additionally reported a shift toward highly aciduric microbial communities in diabetic patients, including increased prevalence of *Streptococcus mutans*, *Lactobacillus* species, and *Candida albicans*. Higher levels of Advanced Glycation End-products (AGEs) were also associated with increased Decayed, Missing, and Filled Teeth (DMFT) scores, suggesting a relationship between systemic oxidative stress and caries severity.

AI Performance in Caries Detection

Studies evaluating AI-based diagnostic systems demonstrated that Deep Learning models, particularly Convolutional Neural Networks (CNNs), achieved high diagnostic accuracy for early caries detection. As summarized in **Tables 1 and 2**, reported Area Under the Curve (AUC) values ranged from **0.88 to 0.92 for** CNN-based architectures, exceeding the diagnostic performance commonly reported for conventional visual and radiographic assessment.

CNN-based systems showed particular effectiveness in identifying early proximal and non-cavitated lesions through detection of subtle radiographic grayscale variations associated with enamel demineralization.

Table1: Comparative analysis of key studies utilizing Artificial Intelligence (AI) for the correlation of dental caries with systemic diabetic indicators. **Performance metrics of AI architectures in caries detection.** Detailed sensitivity and specificity values for identifying carious lesions across various datasets

Study Reference	AI Architecture	Primary Objective	Performance Metrics	Key Finding/Conclusion
Szabó et al. (2025)	Convolutional Neural Network (CNN)	Automated caries detection in bitewing radiographs	**AUC: 0.92**; Sensitivity: 91.0%	AI outmatched specialists in detecting early incipient lesions in diabetic profiles.
Ghanem et al. (2025)	Support Vector Machine (SVC)	Predicting oral complications in diabetic patients	**Accuracy: 0.95**; AUC: 0.91	The "number of decayed/missing teeth" was a top-5 predictor for systemic risk.
Bahammam (2025)	Light GBM & Random Forest	Prediction of caries risk via	**Accuracy: 85.2%**; F1-	LightGBM combined with Boruta feature selection is

Study Reference	AI Architecture	Primary Objective	Performance Metrics	Key Finding/Conclusion
		socio-metabolic data	score: 85.4%	optimal for multi-variable dental datasets.
Hwang & Kim (2022)	Deep Learning (DL)	Diagnostic accuracy for caries in systemic disease	**Sensitivity: 0.85+**; **Specificity: 0.94**	AI standardizes the subjective interpretation of radiographs in high-risk diabetic patients.
NHANES Analysis (2026)	Machine Learning (ML)	Identifying caries clinical subtypes & metabolic links	**N/A** (Pattern Analysis)	Identified unique **"socially recognizable"** clusters of sugar-laden diet links in diabetic cohorts.

Table 2: Performance metrics of Machine Learning (ML) and Deep Learning (DL) algorithms in the detection and risk prediction of dental caries in diabetic populations.

AI Model Type	Specific Algorithm	Primary Application	Reported Accuracy/AUC
Deep Learning	CNN (ResNet-50/U-Net)	Radiographic caries detection	0.86 – 0.92 (AUC)
Machine Learning	Random Forest	Caries risk prediction in T2DM	83.4% Accuracy
Machine Learning	LightGBM	Multi-variable metabolic screening	85.2% Accuracy
Machine Learning	XGBoost	Predicting hyposalivation-related decay	84.0% Accuracy

Diagnostic performance of Deep Learning models in caries detection. Comparisons of AUC, IoU, and mAP metrics for different neural network architectures.

Note: **ML:** Machine Learning, **N/A:** Not Applicable, **CNN:** Convolutional Neural Network, **ResNet:** Residual Network (a type of CNN), **SVC/SVM**: Support Vector Classification / Support Vector Machine, **XGBoost:** Extreme Gradient Boosting, **T2DM:** Type 2 Diabetes Mellitus, **AI:** Artificial Intelligence, **AUC:** Area Under the Curve: **DL:** Deep Learning, **DM:** Diabetes Mellitus, **Light GBM**: Light Gradient-Boosting Machine

Predictive Modeling and Multi-Modal Integration

Several studies demonstrated the feasibility of integrating oral health variables with systemic metabolic indicators using Machine Learning models. Models combining DMFT scores, age, and Body Mass Index (BMI) successfully identified individuals at risk of undiagnosed Type 2 Diabetes Mellitus with reported sensitivities approaching **78%.**

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In addition, ensemble learning models incorporating salivary biomarkers and clinical oral parameters identified dental caries status as a significant predictor of glycemic instability. **Table 3** summarizes the principal AI-integrated data modalities and their reported predictive performance.

Table 3 – Multi-Modal AI Input Variables and Systemic Correlation Accuracy**.**

Data Modality	Specific Variables	AI Algorithm	Predictive Outcome	AUC/Accuracy
Clinical Oral Data	DMFT Index, Plaque Index	Random Forest	Risk of Undiagnosed T2DM	0.82 (AUC)
Salivary Omics	Glucose, pH, Cytokines	XGBoost	HbA1c Instability ($> 7.0\%$)	87.5% Acc.
Radiographic Data	Alveolar bone loss + Caries	CNN	Microvascular Risk Flag	0.89 (AUC)
Socio-Behavioral	Diet, BMI, Hygiene frequency	LightGBM	Future Caries Progression	85.2% Acc.

Categorization of AI modalities in the caries-diabetes axis. Classification of computer vision, predictive analytics, NLP, and XAI tools used in precision dentistry.

Note:**BMI:** Body Mass Index, **DMFT:** Decayed, Missing, and Filled Teeth Index, **EHR:** Electronic Health Record, **HbA1c:** Glycated Hemoglobin, **NLP:** Natural Language Processing, **PA:** Periapical (Radiograph), **pH:** Potential of Hydrogen

AI-Driven Opportunistic Screening

AI-assisted radiographic analysis demonstrated potential utility for opportunistic systemic disease screening during routine dental examinations. High-risk caries patterns, particularly cervical and smooth-surface lesions, were associated with increased likelihood of diabetic microvascular complications, including retinopathy and nephropathy.

Furthermore, Explainable Artificial Intelligence (XAI) tools, such as saliency mapping techniques, improved interpretability of AI-generated outputs by visually identifying anatomical regions contributing to algorithmic decision-making. These approaches enhanced clinician confidence and facilitated more targeted medical referral pathways.

IV. Discussion

This systematic review highlights the emerging role of Artificial Intelligence (AI) in bridging the diagnostic gap between oral and systemic health through analysis of the caries-diabetes relationship. A novel aspect of the current evidence is the transition from viewing dental caries solely as a localized oral disease toward considering it a potential biomarker of metabolic dysregulation and systemic inflammatory burden **(2,4,29)**. (Figure 2) The reviewed studies collectively suggest that AI-based models may provide clinically relevant insights extending beyond lesion detection alone.

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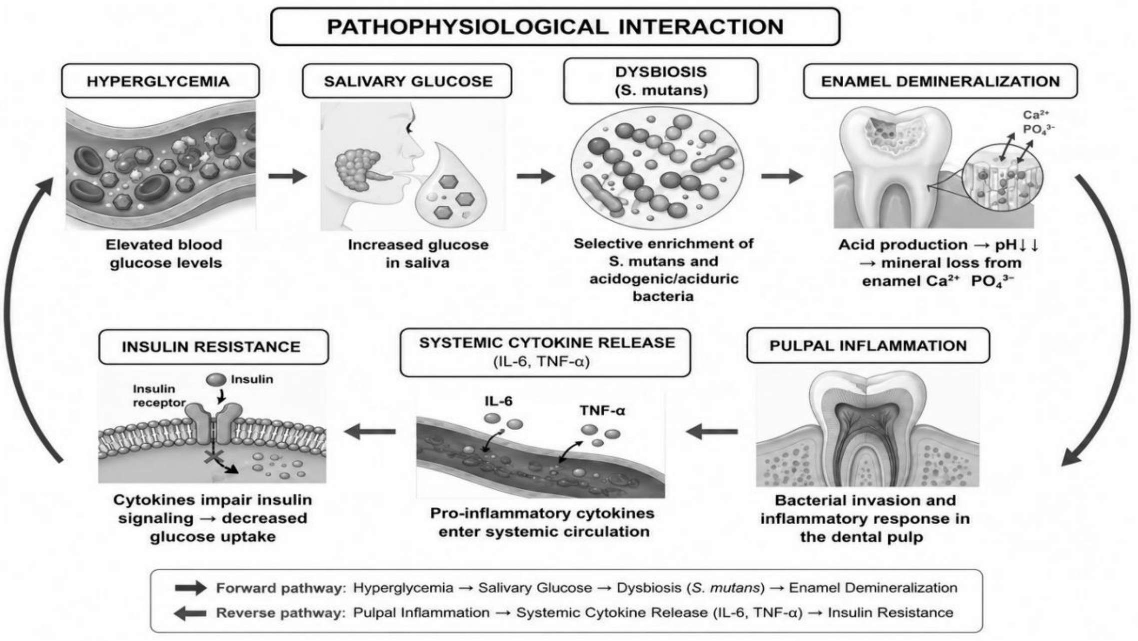

The findings indicate that Deep Learning models, particularly Convolutional Neural Networks (CNNs), demonstrated high diagnostic accuracy for detecting early carious lesions in diabetic patients **(7,19)**. This observation has important clinical implications because diabetic individuals frequently present with altered salivary composition and accelerated enamel demineralization, conditions that may reduce the sensitivity of conventional visual and radiographic examination. AI-assisted analysis therefore offers potential value for earlier identification of high-risk patients and improved preventive intervention strategies **(31,32).**

Another important observation was the growing use of predictive Machine Learning models integrating oral clinical findings, radiographic characteristics, salivary biomarkers, and demographic variables. These multi-modal approaches support the concept of opportunistic screening during routine dental care and reinforce the possibility of using oral health parameters to assist in identifying individuals at risk for undiagnosed diabetes or future glycemic instability **(33,34)**. This represents a meaningful shift from conventional diagnostic dentistry toward predictive and preventive precision oral healthcare.

The present review additionally emphasizes the importance of Explainable Artificial Intelligence (XAI) in improving transparency and clinician confidence. Visual interpretability methods, including saliency mapping, may facilitate clinical acceptance by identifying the anatomical features contributing to AI-generated predictions **(39,40)**. Such developments are essential for future integration of AI-based decision support systems into routine dental practice.

Despite these promising findings, several limitations should be acknowledged. Considerable heterogeneity existed among the included studies regarding AI architecture, dataset size, validation methodology, and outcome reporting. Many studies relied on highly curated imaging datasets acquired under controlled conditions, which may limit generalizability to real-world clinical settings **(37,38)**. Additionally, variability in study design and reporting standards complicated direct comparison of diagnostic performance metrics across investigations.

Clinically, incorporating AI into dental practice fosters interdisciplinary synergy between dentistry and medicine through early metabolic risk detection and personalized prevention **(Table 4)**. Nevertheless, widespread adoption necessitates further prospective multicenter trials utilizing standardized, externally validated datasets. To ensure clinical reliability, reproducibility, and regulatory approval, future studies must prioritize robust validation strategies and transparent AI frameworks.**(39,40).**

Table 4 – Integrated Clinical Workflow for the Diabetic Dental Patient.

Clinical Stage	Actionable AI Integration	Clinical Objective
Initial Screening	ML-based risk assessment (DMFT + BMI + Age)	Identify undiagnosed or poorly controlled DM.
Radiographic Exam	CNN-assisted bitewing analysis	Detect incipient proximal lesions in xerostomic patients.
Preventive Phase	AI-generated **"Caries Activity"** prediction	Tailor fluoride and antimicrobial frequency.
Maintenance	Remote monitoring via intraoral photography AI	Track **"white spot"** lesion remineralization.

Integrated clinical workflow for the diabetic dental patient. A step-by-step protocol for AI-assisted risk stratification and interprofessional medical-dental referrals.

Note: **DSS:** Decision Support System, **FDI:** Fédération DentaireInternationale (World Dental Federation), **MDI:** Medical-Dental Integration, **ppm**: parts per million,
XAI: Explainable Artificial Intelligence

V. Conclusion

The findings of this systematic review support the existence of a significant association between dental caries and diabetes mellitus mediated through metabolic, salivary, and microbial alterations. In relation to the study objectives, the reviewed evidence indicates that Artificial Intelligence-based models, particularly Deep Learning and Machine Learning algorithms, demonstrate promising diagnostic and predictive capabilities for identifying diabetes-associated caries patterns and systemic metabolic risk.

The integration of AI into dental diagnostics may enhance early risk stratification and facilitate interdisciplinary medical-dental screening approaches within diabetic populations. However, the clinical applicability of current AI systems remains limited by dataset heterogeneity, lack of standardization, and insufficient external validation. Future multicenter prospective studies using standardized methodologies are necessary to confirm the reliability and generalizability of these approaches before routine clinical implementation can be recommended.

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