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Artificial Intelligence in Periodontics: A Narrative Review of Clinical Applications, Evidence, and Challenges

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ABSTRACT

Background: Periodontitis is a chronic inflammatory disease that damages the tissues and bone supporting teeth and is linked to systemic conditions[1]. Its diagnosis, staging, and long-term management depend on the integration of clinical, radiographic, and risk-factor data under the 2017 World Workshop staging-and-grading framework[2] — tasks that are time-consuming, examiner-dependent, and well suited to computational support. Artificial intelligence (AI), particularly deep learning for image analysis and machine learning for prediction, has attracted rapidly growing interest in periodontology[3].

Purpose: To narratively synthesize the current evidence on AI applications across the periodontal care pathway, including radiographic detection of bone loss, diagnostic and staging support, risk and prognosis prediction, treatment-response forecasting, supportive care, peri-implant disease assessment, and generative AI tools.

Findings: The most mature application is radiographic analysis. Convolutional neural networks detect and quantify alveolar bone loss on panoramic and periapical radiographs with accuracy comparable to or exceeding experienced dentists in controlled settings[4]. Pooled estimates from a systematic review indicate sensitivity of approximately 87% for detecting periodontal bone loss, though specificity is weaker — 69% in the primary meta-analysis, rising to 76% only after excluding one outlier study[1]. Automated methods can stage periodontitis from radiographs, but radiographic output supplies only part of the information required by the 2017 World Workshop staging-and-grading framework[2]. Machine learning models predict tooth loss and one-year treatment response with moderate-to-good discrimination; external validation remains uncommon, and performance can vary across settings[5]. For peri-implant disease, deep learning models detect radiographic marginal bone loss with high pooled accuracy, but the certainty of evidence has been rated very low and none of the eight studies in the 2026 Odontology review used external validation[6]. An AI-enabled toothbrush with remote coaching improved 6-month outcomes as an adjunct to therapy in a randomized trial[7], and large language models answer periodontal questions at a "good but not excellent" level with readability exceeding that recommended for patient-facing material[8].

Conclusions: AI is a promising adjunct — not a replacement — for the periodontist. Technical performance in retrospective datasets has outpaced demonstration of clinical benefit[6]. Key barriers include small single-centre datasets, absent or weak external validation, inconsistent reference standards, limited calibration and explainability, and unresolved privacy, governance, and workflow questions[1].

INTRODUCTION

Periodontitis is a serious periodontal infection that damages the soft tissues and bone around teeth and is linked to systemic conditions[1]. Its management rests on three pillars that each demand substantial clinical judgment: accurate diagnosis and staging, risk-based treatment planning, and lifelong supportive care. The 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions replaced the former chronic/aggressive dichotomy with a multidimensional staging-and-grading system in which stage reflects severity and management complexity, while grade reflects biological progression and risk of poor outcomes[2]. Staging depends primarily on interdental clinical attachment loss, with radiographic bone loss used when attachment levels are unavailable, and on complexity factors such as furcation involvement; grading incorporates direct or indirect evidence of progression, with smoking and diabetes as modifiers[2]. This framework demands synthesis of multiple data streams per tooth and per patient — precisely the kind of pattern-recognition task at which modern AI excels.

The term artificial intelligence covers a family of techniques. Machine learning (ML) algorithms — logistic regression, random forests, support vector machines, neural networks — learn statistical relationships between input features and outcomes from labelled data, and are typically applied to structured clinical data for classification or prediction. Deep learning, a subclass of ML built on multilayer artificial neural networks, has transformed medical imaging: convolutional neural networks (CNNs) learn hierarchical visual features directly from pixels and are the dominant technique in periodontal imaging research[3]. Generative AI, most prominently large language models (LLMs) such as the GPT family, produces fluent natural-language text in response to prompts and is being explored for patient education, clinical documentation, and knowledge retrieval in dentistry[9]. Each family carries distinct strengths and failure modes, and much of the critical appraisal in this review turns on which technique was used, on what data, and validated how.

This review synthesizes the current evidence on AI applications across the periodontal care pathway and asks a deliberately practical question: which applications are supported by credible evidence, and which remain exploratory?

LITERATURE SEARCH APPROACH

This is a narrative review, not a systematic review. Searches were conducted in October 2026 through scholarly search interfaces indexing PubMed and publisher records, using broad terms including "artificial intelligence periodontics," "deep learning periodontal bone loss," "machine learning periodontal disease prediction," "AI peri-implantitis," and "large language models periodontology." Reference lists of retrieved articles and related-citation trails were followed selectively. Priority was given to recent systematic reviews and meta-analyses, externally validated prediction models, and randomized trials; original diagnostic-accuracy studies were included where they were foundational or widely cited. Study selection was purposive rather than exhaustive, no formal risk-of-bias appraisal or PRISMA flow was performed, and the synthesis should be read accordingly. This approach is appropriate for mapping a fast-moving field, but it cannot exclude publication bias or selective reporting.

CLINICAL APPLICATIONS

Radiographic Detection and Quantification of Bone Loss

The foundational study in this area examined a CNN trained on manually segmented panoramic radiographs. Krois and colleagues used 85 panoramic radiographs yielding roughly 2,000 tooth-focused image segments, with periodontal bone loss (PBL) defined as present at 20% or more of root length as measured by three examiners. The CNN achieved a mean accuracy of 0.81, sensitivity of 0.81, and specificity of 0.81, against 0.76 accuracy for six experienced dentists — a difference that was not statistically significant — while the dentists were markedly more sensitive (0.92) but far less specific (0.63)[4]. Notably, the dentists agreed on the presence of PBL in only about half of the images, underscoring how much examiner subjectivity AI tools might reduce. The study's own caveats are instructive: a small dataset, manually cropped segments rather than full dentitions, and cross-validation without an independent hold-out test set[4].

Subsequent work extended detection to automated staging. A hybrid framework combining deep learning for bone-level detection with conventional image processing classified bone loss per tooth and assigned periodontitis stage according to the 2017 World Workshop criteria, reporting an intraclass correlation of 0.91 against radiologists' diagnoses[10].

Two systematic reviews frame the aggregate picture.

A review in the Journal of the American Dental Association identified six studies of AI for radiographic PBL and concluded that some found no substantial difference between AI and clinicians while others found AI superior — but rated the evidence level as low and algorithm performance as inconsistent, recommending caution[11]. A larger Dentomaxillofacial Radiology review using the APPRAISE-AI quality instrument included 30 studies, of which 10 entered a meta-analysis. Pooled sensitivity for detecting periodontal bone loss or periodontitis on 2D radiographs was 87% (95% CI 80–93%); in the primary analysis pooled specificity was 69% (95% CI 56–80%) and accuracy 82% (95% CI 72–90%), improving to 76% and 84% respectively only after excluding one outlier study. The mean APPRAISE-AI quality score was 55.3, with robustness, reproducibility, and methodological conduct the weakest domains — only seven of thirty studies were rated high quality, and none reached very high quality. The authors' conclusion deserves verbatim weight: models "may not yet be adequate as automated screening tools" without further external validation[1].

The pattern across this literature is consistent: sensitivity for disease-positive findings is good, but specificity is weaker, meaning false positives remain a clinical problem; and the gap between retrospective technical performance and demonstrated utility in routine workflows remains wide. An overview of systematic reviews of panoramic-radiograph AI reported approximately 93% accuracy for periodontal bone loss detection, while cautioning that the underlying systematic reviews were few and heterogeneous[12]. A recent scoping review that screened over 6,300 records similarly found CNNs capable of detecting alveolar bone loss, intrabony defects, furcation involvement, gingivitis, biofilm, and calculus with accuracy comparable to or exceeding dental professionals, alongside persistent concerns about dataset size and diversity[3].

Diagnostic and Staging Support

Beyond binary bone-loss detection, AI systems have been designed to reproduce components of periodontal diagnosis. The hybrid staging framework described above assigns stage from radiographs alone, and recent reviews describe CNN pipelines that grade bone-loss severity, identify furcation involvement, and classify defect patterns on panoramic radiographs, periapical films, and increasingly cone-beam CT[10]. Reported accuracies for radiographic tasks in the 2020–2025 literature typically fall between 0.85 and 0.98, and CBCT-based pipelines report very high accuracy for tooth segmentation and furcation detection[9].

A critical boundary must be drawn here. Radiographic bone loss determines part of the stage, but complete staging under the 2017 framework requires clinical attachment levels, probing depths, and complexity factors, while grading requires progression and risk-factor data[2]. No radiographic AI system constitutes a complete periodontal diagnosis. The honest framing is that these tools automate one input — the radiographic measurement of bone level — with dentist-level or better consistency and far greater speed, potentially improving the completeness of charting rather than replacing clinical assessment.

Risk, Progression, and Prognosis Prediction

Prediction is where ML's structured-data strengths are most relevant to periodontics, and where the evidence is most instructive about the field's central weakness: generalizability.

A systematic review of AI models for predicting periodontitis included eight studies and found that artificial neural networks were the most frequently used algorithm, with good predictive performance across heterogeneous metrics; four studies had low risk of bias on QUADAS-2, but methods were heterogeneous and most designs retrospective[13].

For tooth-level prognosis, a study compared a validated clinical tooth prognostic system against logistic regression and neural network models for 10-year periodontal tooth loss in supportive periodontal care. The models were developed on a London cohort (69 patients, 1,626 teeth) and externally validated on a Pittsburgh cohort (116 patients, 2,792 teeth). On external validation both AI models achieved an area under the curve of 0.89 (95% CI 0.86–0.91) for predicting tooth loss for periodontal reasons within 10 years[5]. This is one of the few periodontal AI studies with genuine external validation, and its structure — tooth-level predictors including probing depth, mobility, furcation involvement, bone loss percentage, and periapical pathology — illustrates a limitation worth noting: the models excluded patient-level factors such as smoking and systemic health, which clinicians consider central to prognosis[5]. (The source article itself contains inconsistencies between its text and tables in reporting several of the models' other performance metrics, so this review relies on its externally validated design and AUC.)

For treatment-response forecasting, a recent study in the Journal of Periodontology used random forest models to predict whether a patient would achieve a validated clinical endpoint — at most four sites with probing depth of 5 mm or deeper — one year after periodontal treatment. The models were trained on data from

six randomized trials in South America (414 patients) and tested on two trials in North America and Europe (78 patients). Discrimination on external testing was moderate, with an AUROC of 0.76[14]. The design is a retrospective prediction analysis of trial data — not a randomized trial of AI-guided care — and it illustrates how performance established in development settings may not transfer to new populations and disease distributions.

Treatment Planning and Supportive Care

For treatment planning, AI-guided decisions in periodontics remain, with few exceptions, an extrapolation from the prediction literature above: models that forecast response or tooth loss could in principle inform decisions about extraction versus retention, antibiotic adjuncts, recall intervals, and referral timing. The treatment-response model described above found that clinical features carried the greatest collective importance, followed by treatment-related factors — including antibiotic regimen details — with microbiological and demographic features contributing less[14]. The appropriate interpretation is not that AI can tell the clinician which regimen to prescribe; it is that baseline clinical burden and treatment variables are the dominant predictors of the model's chosen endpoint. The studies reviewed here do not establish that AI-driven treatment selection improves patient outcomes.

Supportive care is where the strongest interventional evidence has emerged. A single-centre randomized trial in 100 patients with generalized stage II/III periodontitis compared guideline-conform therapy plus standard oral hygiene advice against the same therapy plus an AI-enabled multimodal-sensing toothbrush with remote clinician micromessaging. At six months, the proportion of inflamed periodontal pockets fell from 81.4% to 44.4% in the intervention group versus 80.7% to 52.3% in controls — a between-group difference of 7.9 percentage points (95% CI 1.6–14.6) — with better oral hygiene levels and no significant adverse events[7]. The trial is notable as one of the first randomized demonstrations of an AI-adjacent digital intervention improving periodontal outcomes as an adjunct to therapy. Its limits are equally notable: the intervention bundled a sensing toothbrush with clinician messaging, so the benefit cannot be attributed to the AI component alone; the trial was single-centre; and six-month pocket resolution is not evidence of long-term supportive-care effectiveness.

Peri-Implant Disease

Peri-implantitis is methodologically attractive for AI because radiographic marginal bone loss is central to its case definition, and implants are radiographically conspicuous. The evidence nevertheless remains early.

A 2026 systematic review in Odontology identified eight studies, all retrospective, single-centre investigations published between 2021 and 2025. Binary classifiers reported sensitivities up to 0.90–0.98 and specificities up to 0.95, and segmentation models achieved Dice coefficients above 0.97 — but every study showed high risk of bias in patient selection and index-test domains, relied exclusively on internal validation, and used heterogeneous diagnostic targets. The certainty of evidence was graded as very low, and the authors concluded that AI-based peri-implant diagnostic systems should be considered investigational[6].

Meta-analyses provide pooled estimates for related radiographic targets. One meta-analysis of five studies totalling 12,545 periapical and panoramic radiographs found pooled sensitivity of 88%, specificity of 91%, and an AUC of 0.95 for detecting peri-implant marginal bone loss[15]. Another of nine studies and 7,284 participants reported pooled sensitivity of 0.84 (95% CI 0.72–0.91), specificity of 0.91 (95% CI 0.81–0.96), and AUC of 0.94 (95% CI 0.91–0.96), with AI showing significantly higher specificity than dentists (pooled dentist specificity 0.70) — though the authors themselves caution that this comparison rested on limited data[16]. Two boundaries must hold: these figures describe detection of radiographic marginal bone loss, not a complete peri-implantitis diagnosis, which requires clinical signs such as bleeding on probing and peri-implant pocket depth; and none of the eight studies in the 2026 Odontology review used external validation, so clinical generalizability is unproven.

Generative AI: Education, Documentation, and Patient Communication

Generative AI applications are the newest and least validated. Two studies from the same group evaluated LLMs against periodontal and peri-implant evidence. In the first, four LLMs — ChatGPT GPT-4.0, Google Gemini, Gemini Advanced, and Microsoft Copilot — answered ten open-ended periodontology questions scored by two periodontists against scientific evidence. All models performed "relatively well," with GPT-4.0 scoring highest and significantly outperforming Gemini (P = .042); the authors concluded that LLMs must not replace dental professionals and that improper use may harm patient care[17]. A companion

study using the same four models on ten peri-implant disease questions found a different ordering, with Gemini Advanced ranking highest and basic Gemini scoring worst, the difference between the two being statistically significant (P = .005)[18]. The divergence between the two studies is itself informative: LLM rankings depend on the question set and on the specific model versions tested, which change quickly.

Patient-facing quality is more concerning. A cross-sectional evaluation posed 48 real periodontal patient questions drawn from public forums to three publicly accessible LLMs. Three expert periodontists scored responses using a structured quality instrument: mean scores landed in the "good" band but at its lower boundary, with no model reaching "very good" or "excellent." Readability was worse — responses required roughly a grade 10–11 reading level against the grade-8 level recommended for public health information[8]. The practical implication is that current LLMs can produce broadly accurate but insufficiently accessible patient-facing periodontal information, and that quality varies across model versions and versions date quickly.

EVIDENCE SUMMARY TABLE

EVIDENCE QUALITY, LIMITATIONS, AND IMPLEMENTATION BARRIERS

The consistent signature of this literature is high technical performance in controlled, retrospective, single-centre settings coexisting with weak evidence of clinical benefit. Several recurring methodological problems explain why.

First, validation. External validation remains a major limitation: all eight studies included in the 2026 peri-implant review relied exclusively on internal validation and carried high risk of bias in patient selection and index-test domains[6]. A periodontal treatment-response model achieved an external-testing AUROC of 0.76 in 78 patients from two trials outside its development setting[14]. These findings support evaluating models in their intended clinical settings, but do not establish why performance differs between settings. Patient-level separation is another important safeguard: multiple images from the same patient must be kept together in training or test splits to avoid inflated performance, and the foundational Krois study explicitly did so[4].

Second, reference standards. AI models are typically trained against annotations by a small number of clinicians — which builds in the examiners' own subjectivity, and where inter-examiner agreement is only moderate, the "ground truth" is itself noisy. The APPRAISE-AI review found that more than half of studies using expert annotations never compared model performance with clinicians in a blinded fashion[1]. Calibration — whether a predicted 30% risk actually corresponds to a 30% event rate — is rarely reported, yet it is decisive for clinical utility[14].

Third, scope. Radiographic bone-loss detection is not periodontal diagnosis: staging requires clinical attachment and probing data, and grading requires progression history and risk factors[2]. Models that exclude patient-level variables — smoking, diabetes, socioeconomic context — may perform well statistically while missing determinants clinicians weight heavily[5]. Datasets drawn from public repositories often lack clinical metadata altogether and may carry demographic bias[9].

Fourth, translational gaps. The studies reviewed here rarely demonstrate improved patient outcomes through prospective deployment; the AI toothbrush trial is the clearest exception, and even there the AI component is bundled with behavioural messaging[7]. Explainability, data privacy, medico-legal responsibility for algorithmic error, and integration with practice management and radiology software all remain unresolved, and reviewers of the field flag governance and transparency as prerequisites for adoption[9]. For generative AI specifically, model outputs may contain inaccurate or unverified claims, are version-dependent, and — as the readability study shows — are often pitched at reading levels inaccessible to the patients who most need them[8].

FUTURE RESEARCH PRIORITIES

The literature's weaknesses define its agenda:

- **External, multicentre validation** of existing radiographic bone-loss and peri-implant models on prospectively collected, demographically diverse datasets, with patient-level splits and pre-registered analysis plans.
- **Calibration and decision-analytic evaluation**: reporting calibration curves and net benefit, not only AUROC, and evaluating models at the decision thresholds clinicians would actually use.
- **Prospective outcome trials** testing whether AI-assisted charting, staging, or risk stratification changes management and improves endpoints such as tooth retention and inflamed-pocket resolution — not merely whether AI matches clinicians in retrospective settings.

Table 1

Application	Representative evidence	Design and data	Key result	Caveats
Radiographic bone-loss detection	Krois et al., Sci Rep 2019	CNN; 85 panoramic radiographs, ~2,000 tooth segments; PBL ≥20%	CNN accuracy 0.81 vs dentists 0.76 (not significant)	Small dataset; cropped segments; no independent hold-out set
Radiographic detection (aggregate)	DMFR 2025 systematic review	30 studies; 10 in meta-analysis	Pooled sensitivity 87%; specificity 69% (primary analysis)	Mean quality score 55.3; robustness and reproducibility weak; "not yet adequate as automated screening tools"
Automated staging	Sci Rep 2020 hybrid model	Deep learning + conventional image processing on panoramic radiographs	ICC 0.91 vs radiologists	Radiographs alone cannot assign full stage or grade
Tooth-loss prognosis	Santamaría et al., J Clin Periodontol 2024	LR and neural network; 185 patients, 4,418 teeth; external validation	External-validation AUC 0.89 (95% CI 0.86–0.91)	Patient-level factors excluded; two-centre, compliant-patient cohorts; source article has internal reporting inconsistencies
Treatment-response prediction	J Periodontol 2025	Random forest; 414 development / 78 external patients from 8 RCTs	External-testing AUROC 0.76	Retrospective analysis of RCT data; performance varies across settings
Supportive care	Li et al., J Clin Periodontol 2024	Randomized trial; 100 patients, stage II/III periodontitis	7.9-percentage-point between-group difference in proportion of inflamed pockets at 6 months	Bundled intervention (AI toothbrush + messaging); single centre; adjunct to therapy
Peri-implant disease	Odontology 2026 systematic review	8 studies, all retrospective, single-centre	Sensitivity up to 0.98, specificity up to 0.95; Dice >0.97	All internal validation; high risk of bias; GRADE certainty very low
Peri-implant marginal bone loss (aggregate)	Li et al., J Prosthet Dent 2025	9 studies, 7,284 participants	Pooled sensitivity 0.84, specificity 0.91, AUC 0.94	Radiographic finding only; limited-data dentist comparison
LLM clinical answers	Chatzopoulos et al., J Prosthet Dent 2024	4 LLMs; 10 questions; 2 periodontist raters	All models "relatively well"; GPT-4.0 best (P = .042 vs Gemini)	10-question scope; rankings depend on question set and model version
LLM patient-facing quality	Valente et al., Int J Dent 2026	3 LLMs; 48 real patient questions	Quality "good" borderline; readability grade 10–11 (too difficult)	Cross-sectional; single time point per model

• **Standardized reference standards** and transparent reporting aligned with AI-specific reporting guidelines such as STARD-AI and TRIPOD+AI, with quality appraised using instruments such as APPRAISE-AI, including whether comparisons with clinicians are blinded.

• **Patient-level integration**: models that combine radiographic, clinical, microbiological, and systemic-health data rather than imaging alone.

• **Governance research** for generative AI: evaluation frameworks for patient-facing chatbots, version pinning and monitoring, readability-targeted output, and clear guidance on liability and disclosure.

• **Health-equity evaluation**: performance across age, sex, ethnicity, restoration status, and imaging hardware, before deployment in populations unlike the training data.

CONCLUSION

AI in periodontics has moved from proof of concept to a body of evidence that is broad but shallow: strong technical performance in detecting radiographic bone loss and peri-implant bone change, moderate and externally validated performance in prognosis and treatment-response prediction, early but genuine randomized evidence for AI-enabled supportive-care tools, and emerging but unvalidated generative-AI applications. The most defensible current positioning is as an adjunct that automates measurement, reduces examiner variability, and structures risk — with the clinician retaining diagnostic authority and responsibility. The gap between retrospective accuracy and demonstrated patient benefit remains the field's defining challenge, and closing it — through external validation, calibration reporting, and prospective outcome trials — should determine whether the next five years of AI in periodontics mature from promising to practice-changing.

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