ACCSCIENCE PUBLISHING

Eurasian Journal of Medicine and Oncology

COMMENTARY

Artificial intelligence in periodontal disease management: Opportunities and challenges

Giuseppe Piedigace[1†], Silvia Drago[1†], Alessandro Polizzi[1,2], Giorgia Marmo[1], Marco Mascitti[3], Saturnino Marco Lupi[4], and Gaetano Isola[1,2*]

[1]Department of General Surgery and Surgical-Medical Specialties, School of Dentistry, Univer-sity of Catania, Catania, Italy

[2]International Research Center on Periodontal and Systemic Health "PerioHealth", University of Catania, Catania, Italy

[3]Department of Clinical Specialistic and Dental Sciences, Marche Polytechnic University, Ancona, Italy

[4]Department of Clinical Surgical, Diagnostic and Pediatric Sciences, University of Pavia, Pavia, Italy

Abstract

Artificial intelligence (AI) is increasingly presented as a transformative technology for periodontology, particularly for radiographic bone-loss detection, risk stratification, and personalized follow-up. Yet high performance in retrospective datasets should not be confused with clinical benefit. This Commentary argues that the field should move from celebrating algorithmic accuracy to demonstrating dependable, equitable, and useful decision support in real periodontal workflows. AI should augment—not replace—clinical examination, professional judgment, and patient communication. Priority should be given to representative multicenter datasets, external and prospective validation, interpretable outputs, privacy-preserving data governance, and evaluation of patient-relevant outcomes. The most credible near-term role for AI is therefore a supervised second reader and monitoring aid. Responsible adoption will depend less on increasingly complex models than on transparent evidence, accountable implementation, and sustained clinician oversight.

Keywords: Artificial intelligence; Periodontitis; Periodontal diagnosis; Clinical decision support; External validation; Ethics

[†]*These authors contributed equally to this work.*

***Corresponding author:**
Gaetano Isola
(gaetano.isola@unict.it)

Citation: Piedigace G, Drago S, Polizzi A, *et al*. Artificial intelligence in periodontal disease management: Opportunities and challenges. *Eurasian J Med Oncol.* 2026;10(5):026260310. doi: 10.36922/EJMO026260310

Received: June 26, 2026

Revised: August 12, 2026

Accepted: August 25, 2026

Published online: September 7, 2026

Copyright: © 2026 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. The issue is no longer whether AI can detect patterns

Periodontitis is a prevalent chronic inflammatory disease whose diagnosis and management depend on the integration of clinical examination, radiographic interpretation, risk factors, and longitudinal response to therapy. This combination makes periodontology attractive for artificial intelligence (AI): radiographs provide image data, electronic records contain repeated measurements, and treatment involves decisions that could benefit from consistent risk assessment. Recent studies and reviews have therefore reported applications spanning automated detection of alveolar bone loss,[1] staging support,[2] prediction of disease progression,[3] analysis of biological markers,[4] and personalized maintenance planning.[5,6]

In this context, it is important to distinguish the terms commonly used to describe

AI-based technologies. AI is the broadest concept and refers to machine-based systems capable of performing tasks such as prediction, recommendation, decision-making, and pattern recognition. Machine learning (ML) is a subset of AI in which algorithms learn patterns from data rather than relying solely on explicitly programmed rules.[7] Deep learning (DL) is a further subset of ML based on multilayer neural networks and is particularly suited to complex data such as radiographic images.[8] Generative AI (GenAI) refers to a category of AI techniques capable of generating new content, including text, images, or video, from patterns learned from training datasets.[9] These terms are therefore related but not interchangeable, and their clinical applications and validation requirements may differ.

The conversation, however, has become too easily dominated by technical performance. An algorithm may discriminate cases from controls, outline bone levels, or reproduce an expert label with impressive accuracy, yet still fail to improve care. Retrospective test sets often resemble the data on which models were developed; labels may reflect local conventions; and a statistically strong result may not translate into a better diagnosis, a more appropriate treatment plan, or improved periodontal stability. The relevant question is therefore not simply whether AI can recognize periodontal patterns. It is whether an AI-supported pathway is safer, more reproducible, more equitable, and clinically more useful than the pathway it is intended to assist.

This distinction should shape the next phase of periodontal AI. The field does not primarily need another catalogue of possible applications. It needs a clinically grounded standard for deciding which applications deserve adoption and under what conditions (Figure 1). Our position is that AI should presently be treated as supervised decision support, with its value judged by external validity, interpretability, workflow fit, and patient benefit rather than by accuracy alone.

The contribution of this Commentary is therefore not to introduce another list of technical requirements for trustworthy AI. Rather, we propose a clinically oriented perspective for periodontology that connects model performance with the conditions required for meaningful adoption in practice. In particular, we argue that the value of periodontal AI should be assessed across a continuum extending from algorithmic performance to external validity, workflow integration, changes in clinician decision-making, and ultimately patient-relevant outcomes. Within this framework, we identify supervised second-reader, risk-assessment, and longitudinal monitoring functions as the most plausible near-term roles for AI, while emphasizing that adoption should depend on demonstrated clinical utility rather than technical accuracy alone. This perspective places implementation and accountability—not technological novelty—at the center of periodontal AI evaluation.

2. Where AI can add value now

Radiographic assessment is the most mature use case. DL systems can identify or quantify periodontal bone loss on panoramic and intraoral radiographs, and selected studies have shown performance approaching that of dental professionals.[10] Used as a second reader, such systems could reduce missed findings, standardize measurements, highlight sites that require closer inspection, and support communication with patients. These benefits are especially plausible in busy services, longitudinal follow-up, and settings where specialist expertise is not immediately available.

AI may also support periodontal assessment beyond radiographic detection of bone loss. For example, natural language processing approaches have recently been

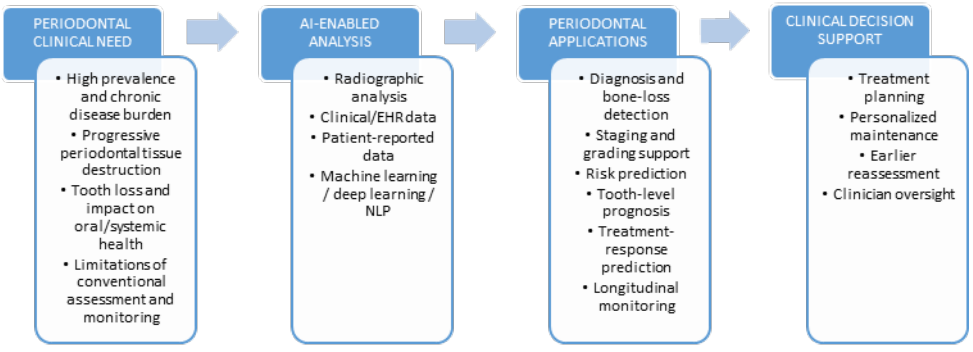


Figure 1. Artificial intelligence in periodontal disease management: from clinical needs to AI-supported applications
Abbreviation: NLP: Natural language processing.

investigated to assist with the classification of periodontitis stage and grade by extracting relevant information from dental charts and clinical notes.[11] Such systems could help clinicians organize complex clinical information and apply the current classification framework more consistently, while remaining dependent on the completeness and accuracy of the underlying clinical records.

At a more granular level, AI-based prediction may also be applied at the tooth level rather than only at the patient level. An ML-based prognostic model has been developed and externally validated to predict 10-year tooth loss in patients with periodontitis receiving supportive periodontal care, illustrating the potential of AI to provide individualized tooth-level prognostic information.[12] Recent ML approaches have also explored the prediction of individual clinical responses to periodontal treatment using demographic, clinical, microbiological, and treatment-related variables.[13] These applications suggest that AI could move beyond diagnosis toward more individualized prognostic assessment, although their predictive performance and generalizability require further independent and prospective validation.

Longitudinal monitoring represents another clinically relevant periodontal application. A recent longitudinal cohort study developed AI models to predict periodontitis progression using clinical and other patient-related variables collected over time.[14] In this setting, AI could function as a monitoring aid by identifying patients, teeth, or periodontal sites showing potentially unfavorable trajectories and prompting earlier clinical reassessment. Such applications may ultimately support individualized maintenance intervals and earlier intervention, provided that their clinical utility is demonstrated in larger, independent, and real-world periodontal populations.

Risk stratification is another credible application, provided that predictions are not detached from clinical context. Combining periodontal measurements with age, smoking, diabetes, previous disease trajectory, adherence, and other relevant variables may help clinicians identify patients who need earlier intervention or shorter recall intervals. The benefit would not arise from replacing established staging and grading, but from making risk information more consistent and more actionable. Similarly, automated comparison of serial records may help detect subtle deterioration and prompt reassessment before substantial damage occurs.

AI may also support individualized care after treatment. Electronic health records, patient-reported information, and remote monitoring tools could be used to identify missed maintenance visits, declining oral-hygiene behaviors, or patterns suggestive of recurrence. Conversational systems might reinforce instructions and answer routine questions, but their role must be carefully bounded. Patient-facing systems should disclose that they are automated, avoid presenting uncertain outputs as diagnoses, and provide a clear route to a clinician. Convenience is useful only when it does not create false reassurance or delay professional evaluation.

Across these applications, the most defensible model is augmentation. The clinician remains responsible for reconciling the AI output with probing findings, radiographic quality, medical history, patient preferences, and the biological complexity of an individual case. An alert without context can increase workload; a probability without explanation can obscure rather than support judgment. AI becomes clinically meaningful only when it supplies information that a practitioner can inspect, challenge, and use.

3. Concrete examples of AI implementation in periodontology

Several recent studies illustrate both the potential and the limitations of AI in periodontology. In the detection of periodontal bone loss on periapical radiographs, an analysis of 21,819 radiographs using five convolutional neural networks reported an overall accuracy ranging from 82.0% to 84.8%, sensitivity from 88.8% to 90.7%, specificity from 66.2% to 71.2%, and an area under the curve (AUC) ranging from 0.884 to 0.913. However, performance varied considerably according to the anatomical region, with accuracy ranging from 94.9% to 96.0% in mandibular anterior teeth compared with 78.0% to 80.7% in maxillary posterior teeth. This finding illustrates how good overall performance may conceal clinically relevant differences across anatomical subgroups.[15]

A second example is provided by a study based on 8,000 periapical radiographs comprising 27,964 teeth, in which a DL model achieved an accuracy of 97.0% for the detection of radiographic bone loss and 92.61% for the assessment of periodontal bone levels. These performances were higher than the mean accuracy of 76–78% reported for the dental professionals involved in the assessment.[16] However, these findings were derived from a retrospective dataset and did not demonstrate that the use of the algorithm resulted in improved treatment decisions or better patient outcomes. Thus, high diagnostic performance should not be interpreted as evidence of clinical benefit.

At the level of aggregated evidence, a recent systematic review and meta-analysis of 30 studies reported a pooled sensitivity of 87%, specificity of 76%, and accuracy of 84% for ML and DL models applied to the detection of periodontal bone loss. Nevertheless, none of the included

studies was classified as having very high methodological quality; 63.3% were rated as having moderate quality and 23.3% as having high quality.[17] These findings suggest that, although diagnostic performance is promising, the methodological quality and standardization of the available evidence remain insufficient to support widespread clinical implementation.

Taken together, these examples illustrate why accuracy alone should not be considered a sufficient clinical endpoint. An algorithm may achieve high accuracy in a development cohort while showing lower performance in specific anatomical regions or remaining untested under prospective, multicenter conditions. The clinical value of AI in periodontology should therefore be determined not only by its ability to classify radiographic findings accurately, but also by its capacity to improve clinical decision-making, reduce diagnostic errors, integrate effectively into clinical workflows, and generate measurable benefits for patients.

4. Integrating radiographic and clinical data

Periodontal AI should not be conceived as a radiographic classifier operating independently from the clinical examination. A more appropriate decision-support system would integrate radiographic features of alveolar bone loss with structured clinical variables, including probing depth, bleeding on probing, clinical attachment level, tooth mobility, furcation involvement, tooth loss, and relevant patient-level risk factors. A multimodal model could generate a patient- or tooth-level risk estimate, while preserving clinician oversight and allowing individual data sources to be reviewed when they disagree. This approach is consistent with the clinical reality that periodontal diagnosis depends on the integration of radiographic and clinical findings rather than on either source alone.[18]

Prospective validation should therefore extend beyond sensitivity and specificity for radiographic bone loss. Priority outcomes should include calibration and predictive performance, agreement between AI-assisted and expert clinical decisions, changes in treatment planning, false-positive and false-negative rates, time required per assessment, clinician workload, and the frequency with which clinicians appropriately override AI recommendations. At the patient level, longitudinal outcomes such as periodontal stability, progression of clinical attachment loss, tooth loss, maintenance adherence, and patient-reported outcomes should also be evaluated. Recent external validation work suggests that specificity and negative predictive value may be particularly informative when AI is used as an adjunctive screening tool, but prospective multicenter studies are still needed to determine whether multimodal AI actually improves clinical decisions and patient outcomes.[19]

5. Why reported accuracy is not enough

Many periodontal AI studies remain retrospective, single-center, or based on small and highly selected datasets.[5,6] These designs are valuable for early development but vulnerable to overfitting and spectrum bias. Differences in imaging devices, exposure parameters, patient populations, disease prevalence, annotation practices, and diagnostic thresholds can substantially change performance. External validation is still uncommon across medical imaging AI, and performance often decreases when an algorithm is tested outside its development environment.[20] Periodontology should assume that the same problem applies until robust evidence shows otherwise.

Ground truth also deserves more scrutiny. A model trained to reproduce one clinician's annotation may learn that clinician's preferences rather than an objective disease state. Consensus labels, clearly specified reference standards, assessment of inter-examiner agreement, and separation of development and validation sites are essential. Reporting only overall accuracy is inadequate when false negatives and false positives have different consequences. Sensitivity, specificity, calibration, subgroup performance, and clinically meaningful decision thresholds should be reported together.

Prospective evaluation is the decisive step. Studies should test not only whether a model performs well, but whether its use changes decisions appropriately, reduces diagnostic variability, saves time without introducing new errors, and improves outcomes that matter to patients. Comparators should reflect actual practice, including clinicians with and without AI assistance. Multicenter datasets must represent variation in age, sex, ethnicity, socioeconomic conditions, comorbidities, disease severity, and care settings. Without this evidence, claims of generalizability are premature. Recent studies provide further evidence that external and clinical validation should precede routine implementation of dental AI. A 2025 multicenter external validation study of a prediction model for periodontal tooth loss demonstrated the feasibility of testing periodontal prediction tools across different clinical centers, highlighting the importance of evaluating model performance beyond the original development population.[21] Similarly, a 2025 clinical evaluation of an AI-based application for measuring alveolar bone loss assessed its performance from the perspective of dental professionals, providing evidence that clinical usability should be considered alongside technical accuracy.[22] More recently, an external validation study of two FDA-cleared AI decision-support systems for

periodontal bone loss reported specificity of 94.23% and 93.55%, but lower concordance of 78.47% and 73.89%, respectively, demonstrating that strong performance in selected metrics does not necessarily imply complete diagnostic agreement.[23] These findings reinforce the need for multicenter, prospective and clinically oriented validation before AI systems are incorporated into routine periodontal decision-making.

Because panoramic radiographs vary substantially in positioning, contrast, density, anatomical coverage, and the presence of artifacts, AI systems should incorporate a predefined input-quality assessment before attempting periodontal interpretation. Rather than relying on a single universal quality score, minimum acceptable quality should be defined according to clinically relevant criteria, including adequate visualization of the dentition and alveolar crest, acceptable patient positioning and exposure, sufficient contrast and sharpness, and absence of artifacts that could obscure periodontal structures.[24] Images that fail predefined thresholds should trigger a quality warning, human review, or exclusion from automated interpretation. Automated quality assessment may represent an additional safety layer, as recent work has demonstrated the feasibility of DL systems for evaluating contrast and density, artifacts, anatomical coverage, patient positioning, and overall panoramic image quality.[25]

6. Representativeness and harmonization of multicenter European datasets

For European periodontal AI datasets, representativeness should include variation in age, sex, ethnicity, geographical setting, socioeconomic background, comorbidities, disease severity, and healthcare setting, as well as variation in imaging equipment and acquisition protocols. These characteristics should reflect the intended clinical population, and model performance should be assessed across relevant subgroups to identify potential disparities.[26]

Differences in diagnostic practices between participating centers should be addressed through standardized data collection procedures and a common case definition established before model development. For periodontitis, the 2017 classification based on staging and grading provides an appropriate framework for harmonizing case definitions across centers.[27] Clinical measurements, radiographic acquisition, annotation procedures, and outcome definitions should be standardized where possible, while center-specific differences should still be documented. Independent expert assessment or consensus should be used to establish the reference standard, and at least one participating center should ideally be reserved for external validation to assess generalizability under genuine between-center variation.[28]

7. Governance is part of clinical performance

Periodontal AI depends on sensitive health information and, increasingly, on linked radiographic, clinical, behavioral, and systemic data. Privacy and security cannot be treated as administrative details added after model development. Data minimization, appropriate consent or other lawful bases, secure storage, access controls, auditable data use, and clear retention policies must be designed into the system. Privacy-preserving approaches, including federated learning, may facilitate collaboration without centralizing all patient-level data, although they do not eliminate governance or bias concerns.[29]

Bias is a clinical safety issue. Under-represented populations may receive less reliable predictions, while historical patterns in care may be encoded as if they were biological truth. Performance should therefore be examined across relevant subgroups and monitored after deployment. A model that is accurate on average but unreliable for a particular population is not ready for indiscriminate use. Institutions also need mechanisms for reporting errors, reviewing unexpected outputs, updating models, and withdrawing systems whose performance deteriorates.

Transparency must extend beyond explainability graphics. Clinicians should know what population a model was trained on, what input quality it requires, what outcome it predicts, how uncertainty is expressed, and where it is known to fail. Responsibility must remain explicit: developers are accountable for design and evidence, institutions for procurement and monitoring, and clinicians for using outputs within their competence and the approved purpose (Figure 2). These obligations reflect the broader principle that opportunities and challenges in dental AI are inseparable.[30]

8. Comparative regulatory perspectives: United States, Europe, and Asia

AI regulation in healthcare varies across jurisdictions, with relevant implications for periodontal research and practice. In the United States, the Food and Drug Administration (FDA) regulates AI-enabled medical devices according to their intended use and risk profile, while recent guidance also addresses planned modifications to AI-enabled devices.[31] In Europe, the EU AI Act adopts a risk-based framework and introduces additional requirements for high-risk AI systems, including risk management, data governance, transparency, human oversight, and post-market monitoring.[32] In Asia, regulatory approaches

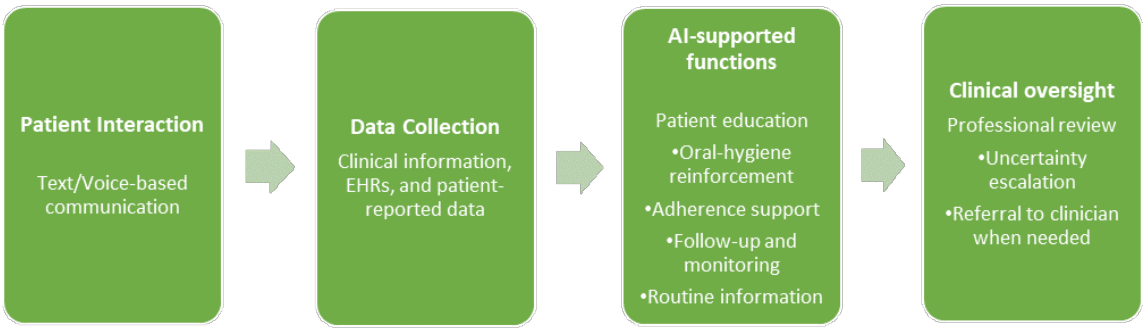


Figure 2. Patient-facing applications of artificial intelligence in periodontal care
Abbreviation: EHR: Electronic health record.

differ among countries; Japan regulates AI-enabled Software as a Medical Device within its existing medical-device framework, while China has developed specific requirements for AI-enabled medical devices under the National Medical Products Administration.[33] These differences may complicate international periodontal research, particularly regarding data sharing, clinical validation, algorithm updates, and post-market surveillance. Researchers and clinicians should therefore consider regulatory requirements from the early stages of AI development and implementation.

9. A practical agenda for responsible adoption

A useful path forward can be summarized in five priorities. First, develop representative multicenter datasets using standardized acquisition, annotation, and outcome definitions. Second, require external and prospective validation before routine clinical use. Third, compare clinician-plus-AI performance with current care and measure workflow effects, downstream treatment decisions, patient experience, and health outcomes. Fourth, make uncertainty and limitations visible to users and preserve a meaningful human review step. Fifth, establish governance for privacy, equity, model updates, incident reporting, and post-deployment surveillance.

The economic implications of AI adoption should be considered alongside its clinical performance. In dental care, the available economic evidence remains limited, but modeling studies suggest that AI-assisted diagnostic pathways may reduce costs when improved detection leads to appropriate downstream management. For example, economic modelling of AI-assisted proximal caries detection estimated costs of €298 per patient compared with €322 for conventional assessment, while also predicting longer tooth retention (64 versus 62 years).[34]

Conversely, economic benefit is not guaranteed. A systematic review of economic evaluations of AI-based oral disease screening reported that, although several modelling studies suggested potential cost savings, the available evidence was heterogeneous and strongly dependent on assumptions regarding diagnostic accuracy, treatment pathways, and long-term outcomes.[35] These findings highlight the importance of evaluating downstream clinical consequences rather than assuming that improved diagnostic performance will automatically translate into economic or patient benefit.

For dental practices, implementation costs may include software acquisition, integration with existing imaging and practice-management systems, staff training, technical support, data governance, and ongoing maintenance. Possible financing approaches include subscription-based software-as-a-service, pay-per-use arrangements, or licensing through larger dental groups and networks. However, evidence comparing these financing models in dentistry remains scarce. Practices should therefore assess the total cost of ownership and determine whether the expected clinical and operational benefits justify the investment. Future studies should incorporate cost-effectiveness and budget-impact analyses alongside clinical validation, including direct implementation costs, workflow effects, treatment consequences, and patient-relevant outcomes.[36]

Education must develop in parallel. Periodontists do not need to become software engineers, but they should understand the difference between discrimination and calibration, recognize dataset shift, interpret uncertainty, and identify automation bias. Training programs should teach clinicians how to question an output and document when it influences care. Patients should be told when AI contributes to assessment or communication and should retain the opportunity to discuss the result with a qualified professional.

These requirements are not barriers to innovation. They are what allow innovation to become trustworthy care. Well-governed AI could reduce variability, extend specialist support, and strengthen preventive and personalized periodontology (Figure 3). Poorly validated AI could instead amplify bias, generate unnecessary referrals, miss disease, or weaken accountability. The discipline should therefore reward evidence of clinical utility and responsible implementation, not novelty alone.

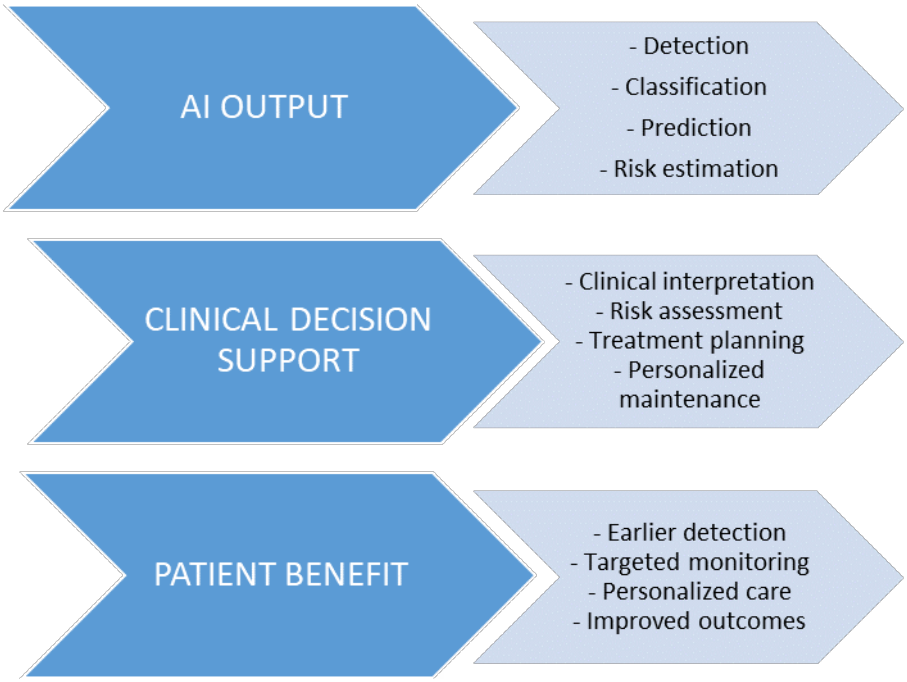


Figure 3. From AI output to clinical value in periodontology

10. Conclusions

The near-term future of AI in periodontology is likely to be quieter than the rhetoric of transformation suggests: a second reader for radiographs, a structured aid for risk review, and a monitoring tool that draws attention to change. That is still meaningful progress. AI should be adopted when it helps clinicians see more consistently, act earlier, and communicate more clearly—while leaving clinical responsibility where it belongs.

Acknowledgments

None.

Funding

This work was funded by the Italian Ministry of Health (grant PNRR-POC-2023-12377354) granted to G.I. This work was also supported by the European Union's NextGenerationEU initiative under the Italian Ministry of University and Research as part of the PNRR—M4C2-I1.3 Project PE00000019 "HEAL ITALIA," CUP I53C22001440006, awarded to A.P.

Conflict of interest

Both Alessandro Polizzi and Gaetano Isola are the Editorial Board Members of this journal, but they were not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. The authors declare no conflicts of interest.

Author contributions

Conceptualization: Gaetano Isola
Funding acquisition: Gaetano Isola
Supervision: Gaetano Isola
Writing–original draft: Giuseppe Piedigace, Silvia Drago
Writing–review & editing: All authors

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Not applicable.

Further disclosure

During the preparation of this manuscript, the authors used AI-assisted tools only for language editing. The authors reviewed and edited all AI-assisted output and take full responsibility for the content of the submitted manuscript.

References

1. Khormali A, Soghli N, Miguez PA. Guiding the AI revolution in periodontology and implant dentistry: Concepts, ethics, accountability, and a roadmap for sustainable adoption. *Periodontol 2000*. Published online August 31, 2026.

   doi: 10.1111/prd.70078

2. Chang HJ, Lee SJ, Yong TH, *et al*. Deep Learning Hybrid Method to Automatically Diagnose Periodontal Bone Loss and Stage Periodontitis. *Sci Rep*. 2020;10(1):7531.

   doi: 10.1038/s41598-020-64509-z

3. Te Lin Y, Li C, Korostoff J, Fiorellini JP, Yang J, Chang YC. Three-dimensional digital quantitative analysis of periodontal and peri-implant phenotype-A narrative review. *Periodontol 2000*. Published online July 11, 2025.

   doi: 10.1111/prd.12639

4. Kageyama S, Hama S, Furuta M, *et al*. Performance of salivary microbiota in detecting periodontitis using a machine learning approach. *Front Cell Infect Microbiol*. 2025;15:1631798.

   doi: 10.3389/fcimb.2025.1631798

5. Pitchika V, Büttner M, Schwendicke F. Artificial intelligence and personalized diagnostics in periodontology: a narrative review. *Periodontol 2000*. 2024;95(1):220-231.

   doi: 10.1111/prd.12586

6. Polizzi A, Quinzi V, Lo Giudice A, Marzo G, Leonardi R, Isola G. Accuracy of artificial intelligence models in the prediction of periodontitis: a systematic review. *JDR Clin Trans Res*. 2024;9(4):312-324.

   doi: 10.1177/23800844241232318

7. Ting Sim JZ, Fong QW, Huang W, Tan CH. Machine learning in medicine: what clinicians should know. *Singapore Med J*. 2023;64(2):91-97.

   doi: 10.11622/smedj.2021054

8. Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI. *J Magn Reson Imaging*. 2019;49(4):939-954.

   doi: 10.1002/jmri.26534

9. Rouzrokh P, Khosravi B, Faghani S, *et al*. A Current Review of Generative AI in Medicine: Core Concepts, Applications, and Current Limitations. *Curr Rev Musculoskelet Med*. 2025;18(7):246-266.

   doi: 10.1007/s12178-025-09961-y

10. Krois J, Ekert T, Meinhold L, *et al*. Deep learning for the radiographic detection of periodontal bone loss. *Sci Rep*. 2019;9:8495.

    doi: 10.1038/s41598-019-44839-3

11. Ameli N, Firoozi T, Gibson M, Lai H. Classification of periodontitis stage and grade using natural language processing techniques. *PLOS Digit Health*. 2024;3(12):e0000692.

    doi: 10.1371/journal.pdig.0000692

12. Santamaria P, Troiano G, Serroni M, Araùjo TG, Ravidà A, Nibali L. Exploring the accuracy of tooth loss prediction between a clinical periodontal prognostic system and a machine learning prognostic model. *J Clin Periodontol*. 2024;51(10):1333-1341.

    doi: 10.1111/jcpe.14023

13. Feher B, de Souza Oliveira EH, Duarte PM, Werdich AA, Giannobile WV, Feres M. Machine learning-assisted prediction of clinical responses to periodontal treatment. *J Periodontol*. 2025;96(11):1199-1212.

    doi: 10.1002/JPER.24-0737

14. Furquim CP, Caruth L, Chandrasekaran G, *et al*. Developing Predictive Models for Periodontitis Progression Using Artificial Intelligence: A Longitudinal Cohort Study. *J Clin Periodontol*. 2025;52(10):1478-1490.

    doi: 10.1111/jcpe.14194

15. Hoss P, Meyer O, Wölfle UC, *et al*. Detection of Periodontal Bone Loss on Periapical Radiographs-A Diagnostic Study Using Different Convolutional Neural Networks. *J Clin Med*. 2023;12(22):7189.

    doi: 10.3390/jcm12227189

16. Chen CC, Wu YF, Aung LM, *et al*. Automatic recognition of teeth and periodontal bone loss measurement in digital radiographs using deep-learning artificial intelligence. *J Dent Sci*. 2023;18(3):1301-1309.

    doi: 10.1016/j.jds.2023.03.020

17. Khubrani YH, Thomas D, Slator PJ, White RD, Farnell DJJ. Detection of periodontal bone loss and periodontitis from 2D dental radiographs via machine learning and deep learning: systematic review employing APPRAISE-AI and meta-analysis. *Dentomaxillofac Radiol*. 2025;54(2):89-108.

    doi: 10.1093/dmfr/twae070

18. Tichy A, Werner N, Dujic H, *et al*. Artificial Intelligence in Periodontology: A Systematic Review. *J Periodontal Res*. 2026;61(6):639-661.

doi: 10.1111/jre.70107

19. Polizzi A, Nibali L, Santamaria P, Venezia P, Tartaglia G, Isola G. Performance of AI Chatbots in Providing EFP S3-Level Guideline-Based Information for Stage IV Periodontitis. *J Periodontal Res*. Published online 2026.

    doi: 10.1111/jre.70166

20. Yu AC, Mohajer B, Eng J. External validation of deep learning algorithms for radiologic diagnosis: a systematic review. *Radiol Artif Intell*. 2022;4(3):e210064.

    doi: 10.1148/ryai.210064

21. Serroni M, Ravidà A, Santamaria P, *et al*. Multi-Centre External Validation of a Nomogram for 10-Year Periodontal Tooth Loss Prediction. *J Clin Periodontol*. 2025;52(7):1044-1055.

    doi: 10.1111/jcpe.14143

22. Lee SW, Huz K, Gorelick K, *et al*. Evaluation by dental professionals of an artificial intelligence-based application to measure alveolar bone loss. *BMC Oral Health*. 2025;25:329.

    doi: 10.1186/s12903-025-05677-0

23. Farooqi OA, Fru GA, Gong YM, Oswald LE, DeNucci DJ. Evaluation of artificial intelligence-based clinical decision support systems for caries and periodontal bone loss: An external validation study. *J Am Dent Assoc*. 2025.

    doi: 10.1016/j.adaj.2025.11.005

24. Iacob AM, Castrillón Fernández M, Fernández Robledo L, Barbeito Castro E, Escobedo Martínez MF. Automated Detection of Periodontal Bone Loss in Two-Dimensional (2D) Radiographs Using Artificial Intelligence: A Systematic Review. *Dent J (Basel)*. 2025;13(9):413.

    doi: 10.3390/dj13090413

25. Ameli N, Miri Moghaddam M, Lai H, Pacheco-Pereira C. Automated quality evaluation of dental panoramic radiographs using deep learning. *Imaging Sci Dent*. 2025;55(2):175.

    doi: 10.5624/isd.20240232

26. Collins GS, Moons KGM, Dhiman P, *et al*. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ*. 2024;385:e078378.

    doi: 10.1136/bmj-2023-078378

27. Papapanou PN, Sanz M, Buduneli N, *et al*. Periodontitis: Consensus report of Workgroup 2 of the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions. *J Clin Periodontol*. 2018;45(Suppl 20):S162-S170.

    doi: 10.1111/jcpe.12946

28. Tonetti MS, Greenwell H, Kornman KS. Staging and grading of periodontitis: Framework and proposal of a new classification and case definition. *J Periodontol*. 2018;89(Suppl 1):S159-S172.

    doi: 10.1002/JPER.18-0006

29. Mir BA, Abbas SR, Lee SW. Federated Learning in Healthcare Ethics: A Systematic Review of Privacy-Preserving and Equitable Medical AI. *Healthcare (Basel)*. 2026;14(3):306.

    doi: 10.3390/healthcare14030306

30. Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry: chances and challenges. *J Dent Res*. 2020;99(7):769-774.

    doi: 10.1177/0022034520915714

31. Tang D, Xi X, Li Y, Hu M. Regulatory approaches towards AI Medical Devices: A comparative study of the United States, the European Union and China. *Health Policy*. 2025;153:105260.

    doi: 10.1016/j.healthpol.2025.105260

32. Vokinger KN, Gasser U. Regulating AI in medicine in the United States and Europe. *Nat Mach Intell*. 2021;3:738-739.

    doi: 10.1038/s42256-021-00386-z

33. Zhou K, Gattinger G. The Evolving Regulatory Paradigm of AI in MedTech: A Review of Perspectives and Where We Are Today. *Ther Innov Regul Sci*. 2024;58(3):456-464.

    doi: 10.1007/s43441-024-00628-3

34. Schwendicke F, Rossi JG, Göstemeyer G, *et al*. Cost-effectiveness of Artificial Intelligence for Proximal Caries Detection. *J Dent Res*. 2021;100(4):369-376.

    doi: 10.1177/0022034520972335

35. Sahoo RK, Sinha A, Satpathi S, *et al*. Economic evaluation of AI-based oral disease screening: a systematic review. *Front Med Technol*. 2026;8:1792401.

    doi: 10.3389/fmedt.2026.1792401

36. Wolff J, Pauling J, Keck A, Baumbach J. The Economic Impact of Artificial Intelligence in Health Care: Systematic Review. *J Med Internet Res*. 2020;22(2):e16866.

    doi: 10.2196/16866