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Unveiling AI-Augmented Periodontal Decision-Making: A Comparative Clinical Evaluation of Diagnocat-Based Radiographic Deep Learning and ChatGPT-Driven Treatment Planning Versus Clinical Expert Judgement

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ABSTRACT:
Objective: To evaluate the agreement between periodontal treatment plans generated using a hybrid artificial intelligence (AI) workflow integrating Diagnocat and ChatGPT and clinician-derived consensus treatment plans, and to compare the performance of cone-beam computed tomography (CBCT)-based and orthopantomogram (OPG)-based AI-assisted treatment-planning workflows in patients with Stage II–IV periodontitis.
Methods: This retrospective study included radiographic records of 60 patients diagnosed with Stage II, III, or IV periodontitis. For each patient, CBCT and OPG radiographs were independently analyzed using Diagnocat, an AI-based radiographic interpretation platform. Structured diagnostic reports generated by Diagnocat were converted into standardized clinical summaries and submitted to ChatGPT for generation of evidence-based periodontal treatment plans. Three experienced periodontists independently evaluated the same cases and established consensus treatment plans, which served as the reference standard. Agreement, sensitivity, specificity, accuracy, Cohen's kappa coefficient (κ), receiver operating characteristic (ROC) curve analysis, and area under the curve (AUC) were calculated using IBM SPSS Statistics Version 27.0.
Results: The CBCT-based AI workflow demonstrated higher agreement with clinician-derived consensus treatment plans than the OPG-based workflow (76.7% vs. 65.0%). Agreement between AI-generated and clinician-derived treatment plans was higher for the CBCT-based workflow ($\kappa = 0.52$) than for the OPG-based workflow ($\kappa = 0.38$). The CBCT-based workflow achieved a sensitivity of 82%, specificity of 74%, and overall accuracy of 76.7%. Receiver operating characteristic analysis demonstrated an area under the curve (AUC) of 0.78 (95% confidence interval: 0.68–0.88), indicating acceptable treatment-planning performance.
Conclusion: The integration of Diagnocat and ChatGPT demonstrated promising performance as an AI-assisted periodontal treatment-planning workflow. CBCT-based analysis showed superior agreement and treatment-planning performance compared with OPG-based analysis, highlighting the value of three-dimensional imaging in AI-assisted clinical decision support. Although the hybrid AI workflow demonstrated encouraging results, clinician oversight remains essential for periodontal treatment planning.

KEYWORDS: Artificial intelligence; ChatGPT; Diagnocat; Periodontitis; Periodontal treatment planning; Cone-beam computed tomography; Orthopantomography; Clinical decision support.

INTRODUCTION
Artificial intelligence (AI) has emerged as one of the most influential technological advancements in modern healthcare, transforming disease diagnosis, treatment planning, and clinical decision-making. Through the application of machine learning (ML) and deep learning (DL) algorithms, AI systems can process large volumes of clinical and imaging data, identify complex patterns, and generate predictive outputs that support healthcare professionals in delivering more accurate and efficient care.[1–3] The integration of AI into diagnostic imaging has gained particular attention because of its ability to enhance consistency, reduce observer variability, and improve diagnostic performance.[4]
Among the various AI methodologies, deep learning models based on convolutional neural networks (CNNs) have demonstrated remarkable success in radiographic image interpretation. CNNs can automatically extract relevant imaging features and perform complex pattern-recognition tasks with minimal human intervention.[5,6] Consequently, AI-assisted image analysis has become increasingly important in dentistry, where radiographic evaluation plays a fundamental role in diagnosis and treatment planning.

In dental practice, AI applications have expanded rapidly over the past decade. Numerous studies have reported successful implementation of AI systems for the detection of dental caries, periapical lesions, impacted teeth, root fractures, periodontal bone loss, and maxillofacial abnormalities.[7–10] In addition to diagnostic support, AI technologies have demonstrated potential applications in risk assessment, treatment planning, prognosis prediction, and patient communication.[11] These developments suggest that AI-based systems may contribute to more standardized and evidence-based clinical decision-making.

One of the most widely utilized AI-powered radiographic analysis platforms in dentistry is Diagnocat (DGNCT LLC, Miami, FL, USA). Diagnocat employs deep learning algorithms for automated interpretation of panoramic radiographs, intraoral radiographs, and cone-beam computed tomography (CBCT) scans. The software generates structured diagnostic reports by identifying a wide range of dental and periodontal findings, including alveolar bone loss, furcation involvement, periodontal defects, missing teeth, periapical pathology, and other clinically relevant conditions.[12–14] Previous investigations have demonstrated promising diagnostic performance of AI-assisted radiographic interpretation systems in identifying periodontal and dental pathologies.[13,15] However, most available studies have focused primarily on diagnostic detection rather than comprehensive periodontal treatment planning and clinical decision-making.

Periodontitis is a chronic multifactorial inflammatory disease characterized by progressive destruction of the supporting structures of the teeth and remains one of the leading causes of tooth loss worldwide.[16] The 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions introduced a contemporary staging and grading framework that improved diagnostic precision and facilitated individualized treatment planning.[17,18] Accurate periodontal diagnosis and treatment planning require comprehensive assessment of disease severity, alveolar bone loss, furcation involvement, defect morphology, tooth prognosis, and overall treatment complexity. Consequently, treatment planning often depends heavily on clinician expertise and interpretation of clinical and radiographic findings, resulting in potential inter-clinician variability.[19,25] AI-assisted radiographic interpretation systems may help clinicians identify periodontal findings more consistently and support decision-making during treatment planning.

The emergence of large language models (LLMs) has introduced a new dimension to AI-assisted clinical decision support. ChatGPT (OpenAI, San Francisco, CA, USA) is a generative AI model capable of processing structured information and generating contextually relevant recommendations through advanced natural language processing.[20] In dentistry, ChatGPT has demonstrated potential applications in patient education, clinical documentation, research support, diagnostic assistance, and treatment planning.[21–23] Despite growing interest in the use of LLMs within healthcare, evidence regarding their application in periodontal treatment planning remains limited.

Furthermore, imaging modality may significantly influence AI-assisted diagnostic interpretation and subsequent treatment recommendations. While orthopantomography (OPG) remains one of the most commonly utilized imaging modalities in routine periodontal practice because of its accessibility and lower cost, CBCT provides three-dimensional visualization of periodontal structures and enables superior assessment of alveolar bone morphology, furcation involvement, and osseous defects.[24] Previous studies have reported greater diagnostic accuracy of CBCT compared with conventional two-dimensional imaging modalities for periodontal evaluation and treatment planning.[24]

To date, limited evidence exists regarding the combined use of AI-based radiographic interpretation platforms and large language models for comprehensive periodontal diagnosis and treatment planning. AI-assisted systems have the potential to facilitate identification of periodontal findings and support clinicians in developing more consistent treatment recommendations based on radiographic information. Moreover, the influence of radiographic modality on AI-assisted diagnostic interpretation and subsequent treatment planning remains insufficiently investigated.

Therefore, the aim of this retrospective study was to evaluate the agreement between periodontal treatment plans generated using ChatGPT based on Diagnocat-derived CBCT and OPG reports and the consensus treatment plans formulated by experienced periodontists. The study further investigated whether the use of CBCT-derived diagnostic information resulted in greater concordance between AI-generated and clinician-derived treatment recommendations compared with OPG-derived information. Furthermore, the overall treatment-planning performance of CBCT-based and OPG-based Hybrid AI workflows was compared in patients diagnosed with Stage II, III, and IV periodontitis according to the 2017 World Workshop Classification of Periodontal and Peri-Implant Diseases and Conditions.

2. MATERIALS AND METHODS

2.1. Ethical Approval

The study protocol (Approval No. IPDC/SS/2026/804E) was approved by the Institutional Ethics Committee of Inderprastha Dental College and Hospital, Ghaziabad, Uttar Pradesh, India. The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki for research involving human participants.[22] As this was a retrospective study utilizing anonymized radiographic records, no additional radiographic examinations were performed specifically for research purposes.

2.2. Data Collection

This retrospective study analyzed radiographic records of 60 patients diagnosed with Stage II, III, or IV periodontitis according to the 2017 World Workshop Classification of Periodontal and Peri-Implant Diseases and Conditions.[17,18]

The radiographic records were retrieved from the Department of Periodontology, Inderprastha Dental College and Hospital, Ghaziabad, India. All radiographs were de-identified prior to analysis. Anonymization was performed by removing patient identifiers from image records and assigning a unique study code to each case.

Only patients with both cone-beam computed tomography (CBCT) and orthopantomogram (OPG) radiographs available in institutional records were included in the study. The radiographic examinations had originally been obtained as part of routine diagnostic and treatment-planning procedures and were not acquired specifically for research purposes. CBCT and OPG examinations were not necessarily performed on the same date.

Radiographs were considered eligible for analysis if they demonstrated diagnostically acceptable image quality and allowed assessment of periodontal bone levels, furcation involvement, vertical defects, horizontal defects, and other periodontal findings relevant to treatment planning. Images exhibiting severe artifacts, distortion, incomplete visualization of periodontal structures, poor diagnostic quality, or incomplete records were excluded from analysis.

2.3. Imaging and Diagnocat Analysis

Each radiographic dataset was assigned a unique study identifier and uploaded to Diagnocat (DGNCT LLC, Miami, FL, USA), an artificial intelligence–based radiographic analysis platform utilizing deep learning and convolutional neural network algorithms for automated dental image interpretation.[12–14]

The software automatically generated structured radiographic reports identifying periodontal and dental findings, including alveolar bone loss, vertical and horizontal periodontal defects, furcation involvement, calculus deposits, missing teeth, periapical lesions, and other radiographically detectable abnormalities.

No manual image enhancement, segmentation, contrast modification, brightness adjustment, or region-of-interest selection was performed prior to analysis. All radiographs were evaluated using the default software settings.

For every patient, CBCT and OPG datasets were analyzed independently, generating separate AI-derived radiographic reports for each imaging modality.[12,24]

2.4. AI-Assisted Treatment Planning

The structured diagnostic reports generated by Diagnocat were converted into standardized text-based clinical summaries and subsequently submitted to ChatGPT (OpenAI, San Francisco, CA, USA).[20]

The same prompt template was applied to all cases to ensure consistency of AI-generated treatment recommendations. The language model was instructed to generate evidence-based periodontal treatment plans exclusively on the basis of the diagnostic information provided.[21,23]

The generated treatment recommendations included oral hygiene instructions, risk-factor modification, scaling and root planing, non-surgical periodontal therapy, surgical periodontal therapy, regenerative periodontal procedures, extraction recommendations, supportive periodontal therapy, and periodontal maintenance protocols.

Separate treatment plans were generated from CBCT-based and OPG-based Diagnocat reports, allowing comparative evaluation of AI-assisted treatment-planning performance across imaging modalities.

2.5. Human Assessment

The same radiographic datasets were independently evaluated by three experienced periodontists.

To minimize assessment bias, each evaluator reviewed the radiographic findings independently and without access to the AI-generated reports. Treatment recommendations were recorded using a standardized assessment format.

A consensus treatment plan was established when agreement was achieved between at least two of the three evaluators. This consensus-derived treatment plan served as the reference standard (ground truth) against which AI-generated treatment recommendations were compared.[19,25]

2.6. Outcome Measures

The primary outcome measure was the level of agreement between AI-generated periodontal treatment plans and clinician-derived consensus treatment plans.

Secondary outcome measures included comparison of CBCT-based and OPG-based AI-assisted treatment-planning performance, sensitivity, specificity, overall accuracy, Cohen's kappa coefficient (κ), receiver operating characteristic (ROC) curve analysis, area under the ROC curve (AUC), and confusion matrix–based assessment of agreement and disagreement patterns between AI-generated and clinician-derived treatment plans.

2.7. Statistical Analysis

Statistical analysis was performed using IBM SPSS Statistics for Windows, Version 27.0 (IBM Corp., Armonk, NY, USA).

Descriptive statistics were calculated for all study variables. Agreement between AI-generated and clinician-derived treatment plans was assessed using Cohen's kappa coefficient (κ).
Treatment-planning performance was evaluated using sensitivity, specificity, overall accuracy, and confusion matrix analysis. Receiver operating characteristic (ROC) curve analysis was performed to assess discriminatory performance, and the area under the curve (AUC) with corresponding 95% confidence intervals was calculated.[6, 13]
The overall study workflow is illustrated in Figure 1.

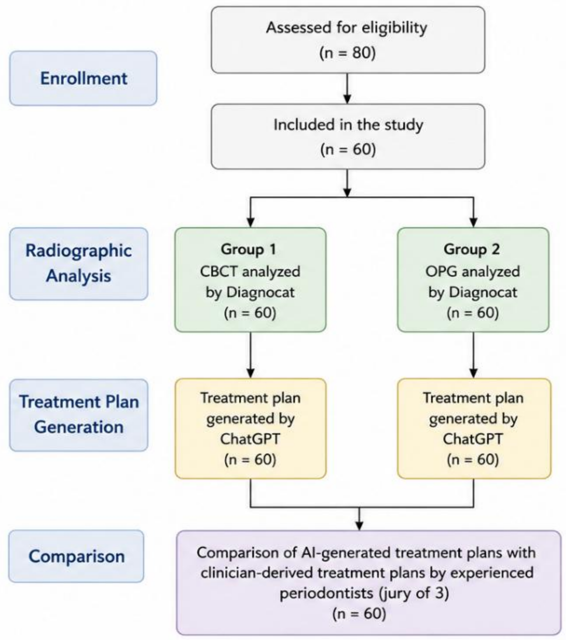


Figure 1. Study workflow and design. Sixty participants were included and divided into Group 1 (CBCT) and Group 2 (OPG). Radiographs were analyzed by Diagnocat, treatment plans were generated by ChatGPT, and AI plans were compared with clinician-derived plans by a panel of three experienced periodontists.

3. RESULTS

In this retrospective study, the performance of a hybrid artificial intelligence workflow integrating Diagnocat and ChatGPT was evaluated using radiographic records from 60 patients diagnosed with Stage II–IV periodontitis. For each patient, both cone-beam computed tomography (CBCT) and orthopantomogram (OPG) radiographs were available and independently analyzed. AI-generated treatment plans were subsequently compared with clinician-derived consensus treatment plans established by three experienced periodontists.

3.1. Agreement Between AI-Assisted and Clinician-Derived Treatment Plans

Agreement between AI-generated treatment plans and clinician-derived consensus treatment plans across imaging modalities is summarized in Table 1.
The CBCT-based AI workflow demonstrated higher agreement with clinician consensus than the OPG-based workflow. Agreement between treatment plans was observed in 46 of 60 cases (76.7%) for CBCT-derived analyses and in 39 of 60 cases (65.0%) for OPG-derived analyses. Correspondingly, disagreement rates were lower for CBCT-based analysis (23.3%) than for OPG-based analysis (35.0%).

Table 1. Treatment-Planning Agreement Between AI-Generated and Clinician-Derived Consensus Recommendations

Workflow	Agreement n (%)	Disagreement n (%)
CBCT-Based AI Workflow	46 (76.7)	14 (23.3)
OPG-Based AI Workflow	39 (65.0)	21 (35.0)

3.2. Treatment-Planning Performance Metrics of CBCT-Based and OPG-Based AI Workflows

The treatment planning performance metrics of the Hybrid AI workflows are presented in Table 2.
The CBCT-based workflow demonstrated superior performance compared with OPG-based analysis. Sensitivity, specificity, and overall accuracy were 82%, 74%, and 76.7%, respectively, for CBCT-assisted treatment planning. Corresponding values for OPG-assisted treatment planning were 68%, 61%, and 65.0%, respectively.

Table 2. Treatment planning Performance Metrics of CBCT-Based and OPG-Based AI Workflows

Parameter	CBCT Workflow (%)	OPG Workflow (%)
Sensitivity	82	68
Specificity	74	61
Accuracy	76.7	65.0

3.3. Agreement Analysis Using Cohen's Kappa Coefficient

Agreement between AI-generated treatment plans and clinician-derived consensus treatment plans was further evaluated using Cohen's kappa coefficient (Table 3).

The CBCT-based workflow demonstrated greater agreement with clinician consensus ($\kappa = 0.52$) than the OPG-based workflow ($\kappa = 0.38$), indicating improved concordance between AI-generated and clinician-derived treatment recommendations when CBCT-derived diagnostic information was utilized.

Table 3. Agreement Analysis Between AI-Generated and Clinician-Derived Treatment Plans

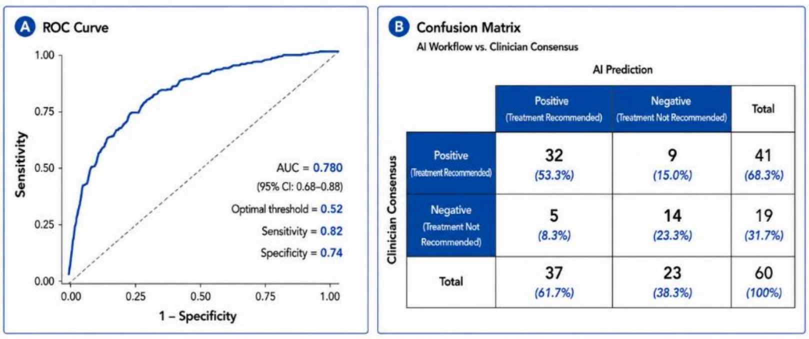
Comparison	Cohen's Kappa (κ)
CBCT AI vs Clinicians	0.52
OPG AI vs Clinicians	0.38

3.4. Overall Treatment-Planning Performance of the CBCT-Based AI Workflow

The overall treatment-planning performance of the CBCT-based Diagnocat–ChatGPT workflow is illustrated in Figure 2.

Receiver operating characteristic (ROC) curve analysis demonstrated an area under the curve (AUC) of 0.780 (95% confidence interval [CI]: 0.68–0.88), indicating acceptable discriminatory performance of the Hybrid AI workflow when compared with clinician-derived consensus treatment plans. The optimal threshold value was 0.52, corresponding to a sensitivity of 82% and specificity of 74%.

The confusion matrix demonstrated 32 true-positive agreements (53.3%) and 14 true-negative agreements (23.3%) between AI-generated and clinician-derived treatment plans, yielding a total of 46 correctly classified cases. Disagreement was observed in the remaining 14 cases, comprising 9 false-negative recommendations (15.0%) and 5 false-positive recommendations (8.3%).Overall, the CBCT-based AI workflow correctly classified 46 of the 60 evaluated cases, resulting in an overall accuracy of 76.7%.



(A) Receiver operating characteristic (ROC) curve demonstrating the performance of the AI workflow. The model achieved an area under the curve (AUC) of 0.780 (95% CI: 0.68–0.88), with an optimal threshold of 0.52, sensitivity of 82%, and specificity of 74%.
(B) Confusion matrix showing agreement and disagreement between AI-generated and clinician-derived treatment plans. Positive agreement (true positives) = 32 (53.3%); negative agreement (true negatives) = 14 (23.3%); false negatives = 9 (15.0%); false positives = 5 (8.3%). Overall accuracy = 46/60 (76.7%).

Figure 2. Overall treatment-planning performance of the Diagnocat–ChatGPT workflow for periodontal treatment planning compared with clinician consensus (N = 60).

4. DISCUSSION

The present study evaluated the performance of a hybrid artificial intelligence workflow integrating Diagnocat and ChatGPT for periodontal treatment planning in patients with Stage II–IV periodontitis. The findings demonstrated that AI-generated treatment plans showed greater agreement with clinician-derived consensus recommendations, with superior performance observed when CBCT-derived diagnostic reports were utilized. The CBCT-based workflow achieved a treatment-planning agreement of 76.7%, whereas the OPG-based workflow demonstrated an agreement of 65.0%. Furthermore, the CBCT-based workflow demonstrated greater agreement with clinician consensus ($\kappa = 0.52$) than the OPG-based workflow ($\kappa = 0.38$), indicating improved concordance between AI-generated and clinician-derived treatment recommendations when CBCT-derived diagnostic information was utilized.

The superior performance observed with CBCT-based analysis may be attributed to the inherent advantages of three-dimensional imaging. Accurate periodontal treatment planning requires detailed assessment of alveolar bone morphology, furcation involvement, intrabony defects, and defect configuration. Conventional two-dimensional radiographs are limited by image distortion, magnification, and anatomical superimposition. In contrast CBCT provides improved visualization of periodontal structures and may facilitate more comprehensive assessment of disease severity and treatment complexity. These factors likely contributed to the higher agreement and diagnostic performance observed in the CBCT-based workflow.

Previous studies evaluating Diagnocat and other deep-learning-based radiographic interpretation systems have reported promising results in the detection of periodontal bone loss, periapical lesions, and other dental abnormalities. However, most investigations have focused primarily on diagnostic performance rather than treatment planning. The present study extends existing evidence by evaluating a complete Hybrid AI workflow in which structured radiographic findings generated by Diagnocat were translated into treatment recommendations using a large language model. This approach more closely reflects real-world clinical decision-making and therefore may have greater clinical relevance.

Receiver operating characteristic analysis demonstrated an AUC of 0.78 for the CBCT-based workflow, indicating acceptable treatment-planning performance. In addition, the workflow achieved a sensitivity of 82%, specificity of 74%, and overall accuracy of 76.7%. These findings suggest that AI-assisted systems may provide clinically useful treatment recommendations when supported by high-quality radiographic information. Nevertheless, discrepancies between AI-generated and clinician-derived treatment plans were observed in a subset of cases, emphasizing that AI systems should currently be regarded as adjunctive tools rather than replacements for professional clinical judgment.

A unique aspect of the present study was the incorporation of ChatGPT into the treatment-planning process. Large language models have demonstrated increasing utility in healthcare applications including clinical documentation, patient education, and decision support. In the present investigation, ChatGPT was able to convert structured radiographic findings into clinically relevant periodontal treatment recommendations. The use of a standardized prompt ensured consistency across all evaluated cases and minimized variability in generated responses.

Certain limitations should be considered when interpreting the findings. The study employed a retrospective design and included a relatively small sample from a single institution, which may limit generalizability. Additionally, treatment planning was based primarily on radiographic findings and did not incorporate complete clinical parameters such as probing depth, clinical attachment level, bleeding on probing, tooth mobility, systemic risk factors, or patient preferences. These variables frequently influence periodontal treatment decisions in routine clinical practice.

Taken together, the integration of Diagnocat and ChatGPT demonstrated promising performance as an AI-assisted periodontal treatment-planning workflow. CBCT-based analysis showed superior agreement with clinician-derived consensus treatment plans compared with OPG-based analysis, highlighting the importance of three-dimensional imaging in AI-assisted decision support. Future multicenter studies incorporating larger datasets and comprehensive clinical parameters are required to further validate the role of AI in periodontal treatment planning.

5. CONCLUSION

Within the limitations of this retrospective study, the integration of Diagnocat and ChatGPT demonstrated promising performance as an artificial intelligence–assisted workflow for periodontal treatment planning. AI-generated treatment recommendations demonstrated agreement with clinician-derived consensus treatment plans and achieved acceptable overall treatment-planning performance, with greater concordance observed for the CBCT-based workflow than for the OPG-based workflow.

The CBCT-based workflow demonstrated superior agreement, sensitivity, specificity, and accuracy compared with the OPG-based workflow, highlighting the importance of three-dimensional imaging in AI-assisted periodontal decision support. These findings suggest that high-quality radiographic information significantly influences the reliability of AI-generated treatment recommendations.

Although the hybrid AI workflow showed encouraging results, discrepancies between AI-generated and clinician-derived treatment plans were observed in a subset of cases. Therefore, AI should currently be regarded as an adjunctive decision-support tool rather than a replacement for clinical expertise and professional judgment. Further prospective multicenter studies incorporating larger patient populations and comprehensive clinical parameters are required to validate and optimize AI-assisted treatment-planning systems for routine periodontal practice.

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