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Role of Artificial Intelligence in Detecting Periodontal Bone Loss on Panoramic Radiography: A Systematic Review

Wlla E. Al-Hammad [1]*, Hala Al Tell [2], Diala Selawi [2], Eman Bani Domi [2], Hadeel Bani Domi [2], Nada Alneserat [2], Aseel Alazzam [2], Tharaa Alrababah [2], Jana Kofahi [2], Nada Al Awadeen [2], Bara' Khalil [2], Ranin Khalafallah [2], Noor Abu Al Samek [2], Saba Alkurdi [2], Lein Al keek [2], Leyan Shahdat [2]

1 Department of Oral Medicine and Oral Surgery, Faculty of Dentistry, Jordan University of Science and Technology, Irbid, Jordan.
2 Faculty of Dentistry, Jordan University of Science and Technology, Irbid, Jordan.

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Correspondence:
Wlla E. Al-Hammad,
Department of Oral Medicine and Oral Surgery, Faculty of Dentistry, Jordan University of Science and Technology, Irbid, Jordan.
wealhammad@just.edu.jo

ABSTRACT

Objectives: Artificial intelligence (AI) is considered a promising tool for enhancing diagnostic accuracy in medicine. Periodontal disease, a highly prevalent oral condition, necessitates early detection to enable timely intervention and prevent progression. This study was designed to assess the effectiveness of AI in identifying periodontal bone loss (PBL) on panoramic radiographs.

Materials and Methods: A systematic literature search was performed following the PRISMA framework. The search strategy, implemented in PubMed, Scopus and Web of Science, combined keywords related to AI, panoramic radiography, and periodontal disease. Study selection proceeded through standardized screening of titles, abstracts, and full texts. The methodological quality of the final included studies was appraised using the Critical Appraisal Skills Programme (CASP) checklist.

Results: The systematic review yielded sixteen studies meeting the inclusion criteria. Based on CASP appraisal, six studies were judged to be of high quality, seven of moderate quality, and three of low quality. Regarding diagnostic performance, the reviewed AI models achieved maximum metrics as follows: accuracy up to 99%, sensitivity up to 100%, and specificity up to 99%. The highest reported area under the curve (AUC) was 95%, while precision and F1-scores both reached peaks of 99%.

Conclusions: AI has demonstrated strong potential in detecting PBL from panoramic radiographs, providing an efficient method for evaluating dental health. Additional clinical studies are necessary to confirm the reliability, consistency, and practical applicability of AI in real-world dental settings.

Keywords: Artificial intelligence, Deep learning, Convolutional neural networks, Panoramic radiography, Periodontal bone loss, Periodontal disease, Diagnosis.

1. Introduction

Periodontitis is a chronic inflammatory disease, highly prevalent and multifactorial in nature, which leads to the breakdown of the tissues supporting the teeth. Its hallmark is the progressive and irreversible destruction of the periodontal ligament, followed by resorption of the alveolar bone. Clinicians rely on this bone loss as the key indicator for assessing disease severity and progression (1). The consequences are not confined to the oral cavity; this damage impairs masticatory function and, critically, is linked through established bidirectional relationships to several systemic health conditions (2,3).

The primary driver of periodontitis is the long-term buildup of microbial plaque and dysbiosis in the dental biofilm. Yet, the severity and pattern of ensuing bone loss are not dictated by bacteria alone. Factors intrinsic to the host, such as the inflammatory response and genetic profile, along with external risks, like smoking and systemic diseases, play a decisive modifying role (4,5). Therefore, to plan effective treatment and secure a positive prognosis, clinicians must accurately diagnose and quantify periodontal bone loss (PBL) at an early stage. While clinical probing is essential, radiographic examination is a critical adjunct, offering a visual record and enabling measurement of osseous changes.

In routine practice, the panoramic radiograph is a common choice. Its utility stems from the broad anatomical view that it provides, patient acceptance due to comfort, and a lower radiation burden compared to a full periapical series (6). A significant drawback, however, lies in its conventional interpretation. The two-dimensional nature of these images introduces distortions and superimpositions, but more importantly, measurements of bone levels are subject to considerable inter-observer subjectivity, undermining consistency and reliability.

In this diagnostic context, the rise of digital technologies offers pathways toward more objective and standardized assessment. For radiographic interpretation, the integration of artificial intelligence (AI), specifically deep learning (DL) methods, is now reshaping how dental images are analyzed. Among these methods, convolutional neural networks (CNNs) have demonstrated strong performance in detecting intricate radiographic patterns. When trained on large, expertly annotated datasets, these models can provide objective, automated diagnostic support for identifying and segmenting areas of PBL, promising improved consistency and efficiency over traditional manual assessment (7-9). Such AI-driven analysis has the potential to enhance reliability, reduce examiner variability, and improve the efficiency of detecting PBL compared with conventional visual assessment.

To the best of our knowledge, only a limited number of systematic reviews have explored how AI performs in detecting PBL from panoramic radiographs. Therefore, this systematic review aims to comprehensively evaluate the current evidence on the accuracy and diagnostic performance of AI-based approaches for assessing alveolar bone loss to make an appropriate treatment plan and determine the prognosis of the disease to achieve successful results.

2. Materials and Methods

A review protocol was specified a priori, outlining the search strategy and protocol, eligibility criteria, data extraction methods, and approaches for quality assessment. The protocol for this systematic review is registered with the Open Science Framework (OSF) under DOI: 10.17605/OSF.IO/AN6TC.

2.1 Research Question

The implementation of AI for the radiographic assessment of periodontal diseases on panoramic radiographs depends on the robustness of evidence derived from clinical research. Thus, this systematic review was conducted to answer one main question, following the PEO framework (Population, Exposure, Outcome): Among patients with or at risk of periodontitis (Population), what is the diagnostic performance of AI models, particularly DL architectures (Exposure), in detecting PBL on panoramic radiographs (Outcome). The primary outcome measures of interest include diagnostic accuracy, sensitivity, specificity, precision, F1-score and area under the curve (AUC).

2.2 Search Strategy and Protocol

A structured search strategy was designed to identify studies investigating the role of AI in detecting PBL on panoramic radiography. Three electronic databases (PubMed, Scopus, and Web of Science) were systematically searched for studies published between 1 January 2015 and 1 January 2026.

The search strategy was developed using various combinations of keywords with the Boolean operators “OR” and “AND.” The complete search strings adapted for each database are presented in Table 1.

Table 1: Database search strings

Database	Full Search String
PubMed	((“Periodontal Diseases”[Mesh)) OR (“Alveolar Bone Loss”[Mesh)) OR (“Periodontitis”[Mesh)) OR (“Periodontal Bone Loss”) OR (“Alveolar Bone Resorption”)) AND ((“Panoramic Radiography”) OR (“Orthopantomography”)) AND ((“Deep Learning”) OR (“Convolutional Neural Networks”) OR (“Artificial Intelligence”) OR (“Machine Learning”))
Scopus	TITLE-ABS-KEY (“Periodontal Diseases” OR “Alveolar Bone Loss” OR “Periodontitis” OR “Periodontal Bone Loss” OR “Alveolar Bone Resorption”) AND TITLE-ABS-KEY (“Panoramic Radiography” OR “Orthopantomography”) AND TITLE-ABS-KEY (“Deep Learning” OR “Convolutional Neural Networks” OR “Artificial Intelligence” OR “Machine Learning”)
Web of Science	((“Periodontal Diseases”) OR (“Alveolar Bone Loss”) OR (“Periodontitis”) OR (“Periodontal Bone Loss”) OR (“Alveolar Bone Resorption”)) AND ((“Panoramic Radiography”) OR (“Orthopantomography”)) AND ((“Deep Learning”) OR (“Convolutional Neural Networks”) OR (“Artificial Intelligence”) OR (“Machine Learning”))

2.3 Eligibility Criteria

We considered full-text, English-language publications that applied AI to panoramic radiographs for the detection of PBL. The search was restricted to English publications, justified by the dominance of English in this technical research domain, the prohibitive risk of error in translating complex AI methodology, and the practical resource constraints of a systematic review. Eligible study designs included diagnostic accuracy studies, cross-sectional studies, and cohort studies. Studies were required to report performance metrics of the AI model. We excluded non-primary research articles, specifically opinion papers, proceeding papers, commentaries, communications, case reports, and review articles. Furthermore, to maintain a focus on panoramic imaging, any study utilizing AI for PBL detection on other radiographic modalities (e.g., periapical or CBCT) was excluded.

2.4 Data Extraction

We followed the PRISMA framework for study selection (Figure 1). Two reviewers performed the initial screening of titles and abstracts independently. Any discrepancies in their assessments were only resolved through discussion with a third, senior reviewer. The relevant articles were subjected to a full-text review by the same reviewers.

This search yielded 32 articles from PubMed (n=24), Scopus (n=6), and Web of Science (n=2). Following the removal of 4 duplicates, 28 records underwent initial screening. At this stage, 9 review articles and 1 conference proceeding paper were excluded. The remaining 18 full-text articles were assessed for eligibility, leading to the exclusion of two studies: one focused on intraoral radiographs and the other had a divergent research aim. Consequently, 16 articles met all inclusion criteria for the qualitative analysis.

The reviewers used a standardized data extraction form that recorded study design, AI methodology, sample size, main study findings, and performance metrics. The quality of the included studies was assessed using the CASP (Critical Appraisal Skills Program) checklist, ensuring a standardized, transparent, and unbiased evaluation process.

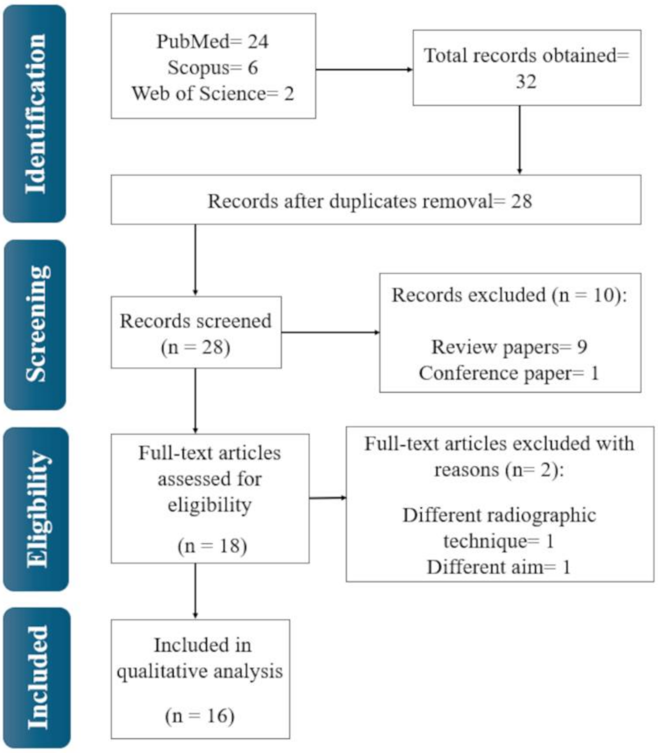

Figure 1: PRISMA framework

3. Results

3.1 Evidence Table

The key data extracted from the sixteen included studies (7-22) is synthesized in Table 2. This summary presents a comparative overview across standardized parameters, including bibliographic information (author, year, country), study design, study sample details, the AI methodology employed, main findings with statistical support, and the assigned evidence quality score.

Table 2: Standardized table of the eligible articles

Author, Year, Country	Study Design	Sample Size	AI Software Used	Main Study Findings	Performance Metrics	Evidence Quality Score
Krois, et al., 2019, Germany (10)	Diagnostic study	2,001 manually cropped image segments from panoramic radiographs	CNN	A CNN trained on a limited amount of radiographic image segments showed at least similar discrimination ability as dentists for assessing PBL on panoramic radiographs	Accuracy= 0.81 Sensitivity (Recall)= 0.81 Specificity= 0.81	8 out of 11 (72.7%)
Kim et al., 2019, South Korea (9)	Cross-sectional study	12,179 panoramic radiographs	DeNTNet	DeNTNet was more effective in detecting PBL on panoramic radiographs than dental clinicians	AUC= 0.95 F1-score= 0.75 Sensitivity (Recall)= 0.87 Specificity= 0.96	6 out of 11 (54.5%)
Chang et al., 2020, South Korea (11)	Diagnostic study	340 panoramic radiographs	Modified Mask RCNN	The model can automatically detect PBL and stage periodontitis with high accuracy and excellent reliability	Accuracy= 0.93	7 out of 11 (63.6%)

Thanahornwong et al., 2020, Thailand (12)	Cohort study	100 panoramic radiographs	Faster RCNN	The application of a faster RCNN to assist in the detection of periodontally compromised teeth may reduce diagnostic effort by saving assessment time and allowing automated screening documentation	F1-score= 0.81 Sensitivity (Recall)= 0.84 Specificity= 0.88	8 out of 12 (66.7%)
Kurt-Bayrakdar et al., 2020, Turkey (13)	Cohort study	2,276 panoramic radiographs	CNN	The CNN system can successfully determine PBL and periodontal disease from panoramic radiographs	Accuracy= 0.91 F1-score= 0.92 Sensitivity (Recall)= 0.94 Specificity= 0.86	10 out of 12 (83.3%)
Jiang et al., 2022, China (14)	Diagnostic study	640 panoramic radiographs	U-Net and YOLO-v4	The DL architecture based on UNet and YOLO-v4 performed well in detecting and clarifying PBL radiologically	Accuracy= 0.77 F1-score= 0.77 Precision= 0.77 Sensitivity (Recall)= 0.77 Specificity= 0.88	6 out of 11 (54.5%)
Ryu et al., 2023, South Korea (15)	Diagnostic study	4,083 panoramic radiographs	RCNN	The proposed DL model successfully detected PBL on panoramic radiographs, demonstrating high diagnostic performance	AUC= 0.91 F1-score= 0.90 Precision= 0.90 Sensitivity (Recall)= 0.91	8 out of 11 (72.7%)
Saylan et al., 2023, Turkey (16)	Diagnostic study	685 panoramic radiographs	YOLO-v5	AI models are effective in identifying PBL, with performance varying by region	Sensitivity (Recall)= 0.75 Precision= 0.76 F1-score= 0.76	9 out of 11 (81.8%)
Ayyildiz et al., 2024, Turkey (17)	Diagnostic study	2,533 panoramic radiographs	Three TL-based CNN models: ResNet50, DenseNet121, and InceptionV3	The models achieved high performance in PBL classification	ResNet50: Accuracy = 0.79 F1-score = 0.69 Precision = 0.69 Sensitivity (Recall)= 0.69 Specificity = 0.84 DenseNet121: Accuracy = 0.79 F1-score = 0.69 Precision = 0.69 Sensitivity (Recall)= 0.69 Specificity = 0.84 InceptionV3: Accuracy = 0.78 F1-score = 0.67 Precision = 0.67 Sensitivity (Recall) = 0.67 Specificity = 0.83	6 out of 11 (54.5%)
Mardini et al., 2024, Chile (18)	Diagnostic study	500 panoramic radiographs	DCNN	DCNN achieved acceptable detection of mild–moderate PBL in cropped molar images, failed to detect severe cases	Weighted F1-score= 0.15 Weighted precision= 0.11 Weighted sensitivity = 0.23	9 out of 11 (81.8%)

					Weighted specificity = 0.26	
Kurt-Bayrakdar et al., 2024, Turkey (19)	Diagnostic study	1,121 panoramic radiographs	U-Net	The model showed promising results in determining PBL patterns and furcation defects from dental radiographs	Accuracy= 0.99 AUC = 0.95 F1-score= 0.99 Precision= 0.99 Sensitivity (Recall)= 1.0	8 out of 11 (72.7%)
Xue et al., 2024, China (20)	Diagnostic study	320 panoramic radiographs	YOLO-v8, Mask RCNN and TransUNet	The proposed DL ensemble model shows high accuracy and efficiency in radiographic detection and a valuable adjunct to periodontal diagnosis	Accuracy= 0.89 F1-score= 0.92 Precision= 0.95 Sensitivity (Recall)= 0.92	9 out of 11 (81.8%)
Jundaeng et al., 2025, Thailand (7)	Cross-sectional study	2,000 panoramic radiographs	YOLO-v8	The YOLO-v8 model can accurately assess PBL and provide individualized periodontal prognoses from panoramic radiographs	Accuracy= 0.98 F1-score= 0.90 Precision= 0.90 Sensitivity (Recall)= 1.0 Specificity= 0.98	9 out of 11 (81.8%)
Rezallah et al., 2025, United Arab Emirates (21)	Diagnostic study	1,417 panoramic radiographic images	Two CNN models: YOLO-v8 and MobileNet-v2	The proposed system provides an efficient and clinically practical diagnostic tool to support the early detection and effective management of periodontitis	MobileNetV2: Accuracy = 0.88 Sensitivity (Recall)= 1.0 YOLO-v8: Precision = 0.74 Sensitivity (Recall)= 0.70	7 out of 11 (63.6%)
Do et al., 2025, Vietnam (8)	Cross-sectional study	500 panoramic radiographs	YOLO-v8	The proposed YOLO-v8 model accurately detects key periodontal landmarks and automates disease staging and grading	Accuracy= 0.99 F1-score= 0.95 Precision= 0.95 Sensitivity (Recall)= 0.94 Specificity= 0.99	10 out of 11 (90%)
Widyaningrum et al., 2025, Indonesia (22)	Diagnostic study	700 Panoramic radiographs	Two-Stage CNN model: Mask RCNN with DenseNet169	The Two-Stage CNN demonstrated robust diagnostic performance for detecting and staging periodontitis in panoramic radiographs	Accuracy = 0.80 F1-score= 0.53 Precision= 0.59 Sensitivity (Recall)= 0.51 Specificity = 0.88	7 out of 11 (63.6%)

CNN: convolutional neural network; PBL: periodontal bone loss; DeNTNet: deep neural transfer network; AUC: area under curve; RCNN: region-based convolutional neural network; DL: deep learning; U-Net: U-shaped convolutional network; YOLO-v4: YOLO model version 4; YOLO-v5: YOLO model version 5; TL-based CNN: transfer learning–based convolutional neural network; ResNet50: residual network with 50 layers; DenseNet121: densely connected convolutional network with 121 layers; InceptionV3: inception model version 3; DCNN: deep convolutional neural network; YOLO-v8: YOLO model version 8; TransUNet: transformers and U-Net hybrid model; MobileNet-v2: mobile network model version 2; DenseNet169: densely connected convolutional network with 169 layers2.

3.2 Study Quality Assessment

We appraised the methodological quality of the included studies using the relevant CASP checklist. The appraisal focused on four domains: relevance, reliability, validity, and applicability. To enable consistent comparison across different study designs, we converted raw scores into percentages. Studies were then categorized as high-quality (≥75%), moderate-quality (55-74%), or low-quality (<55%).

Of the sixteen studies, six were rated as high-quality, with scores ranging from 81.8% to 90%. Seven studies fell into the moderate-quality category (63.6% to 72.7%), while the remaining three were considered low-quality, all scoring 54.5%. Figure 2 shows the quality assessment heatmap of the included studies.

Figure 2: Quality assessment heatmap

3.3 Study Characteristics and Outcome

The sixteen eligible studies (7-22) collectively represented a significant and diverse global sample. The aggregate sample size was substantial, with the number of analyzed panoramic radiographs ranging from 100 (12) to 12,179 (9). Geographically, the research originated from nine countries: four studies from Turkey (13,16,17,19), three from South Korea (9,11,15), two from China (14,20), two from Thailand (7,12), and one each from Germany (10), Chile (18), Indonesia (22), Vietnam (8), and the United Arab Emirates (21). Publication dates spanned from 2019 to 2025.

All included investigations focused on evaluating the efficacy of DL models, specifically various CNN architectures, for the automated detection of PBL. The AI models tested were diverse, ranging from foundational CNNs and segmentation networks, like U-Net to advanced frameworks, such as YOLO (v5 and v8), Faster RCNN, and hybrid systems (e.g., YOLO-v8 with Mask RCNN and TransUNet).

Performance metrics demonstrated generally favorable diagnostic capabilities. The models' overall discriminatory ability, quantified by the AUC and reported across three studies (9,15,19), ranged from 0.91 (15) to 0.95 (9,19). Sensitivity scores, also known as recall, reflecting the accurate detection of diseased sites, spanned from 0.51 (22) to 1.00 (7,19,21). Specificity, indicating correct identification of healthy sites, was robust, ranging from 0.81 (10) to 0.99 (8). Precision ranged from 0.59 (22) to 0.99 (19). The F1-score, balancing precision and recall, varied from 0.53 (22) to 0.99 (19). Notably, two recent studies demonstrated specialized capabilities in automated periodontitis staging and grading, with reported accuracies of 0.89 (20) and 0.99 (8). A major source of this heterogeneity was validation methodology. Only two studies (21,22) performed external validation on independent datasets from different institutions or imaging systems, while the remainder relied on internal validation (e.g., train-test split or cross-validation). Studies lacking external validation reported systematically higher performance metrics, indicating potential overfitting. Furthermore, due to the absence of standardized outcome reporting, some studies omitted AUC or precision-recall curves, hindering direct comparison. These inconsistencies underscore the need for standardized reporting guidelines specific to AI diagnostic studies in dentistry.

4. Discussion

This systematic review evaluated the diagnostic performance of AI models for detecting PBL on panoramic radiographs. Across the included studies, models, such as CNNs, U-Net, RCNN, and YOLO variants, demonstrated generally favorable diagnostic performance, with AUC values frequently exceeding 0.90 in complex tasks, like multi-class classification and image segmentation (9,15,19). The collective findings suggest that these systems might have the potential to identify PBL, differentiate between healthy and diseased sites, and even contribute to staging disease severity, thereby providing a foundation for data-driven clinical decision support (8,20,22).

Notably, some studies found that AI performance was comparable to that of experienced dental clinicians (9,19). This supports the potential role of AI as a supportive tool to mitigate the subjectivity and inter-examiner variability inherent in manual radiographic interpretation, while also improving workflow efficiency through automation (12).

The evolution of this research is marked by a shift from simple detection to more clinically integrated applications. Recent investigations have incorporated advanced tasks, like tooth-level segmentation, identification of the cemento-enamel junction, automated bone-level measurement, and the staging and grading of periodontitis (7,8,20). These developments reflect a move toward implementations that could directly enhance treatment planning and long-term monitoring.

The body of evidence is unified by a shared clinical objective, improving periodontal diagnosis with AI, and a consistent use of panoramic radiographs as the standard imaging modality (7,13,16). This commonality allows the studies to form a coherent narrative despite variations in specific AI models, dataset sizes, and designs.

Methodologically, the field has progressed from earlier studies using binary classification (presence/absence of disease) (9,10) to more recent, sophisticated models that perform detailed, site-specific analysis of bone loss (20,22). This progression from a global to a localized diagnostic focus appears to enhance both accuracy and clinical utility. Furthermore, studies validating AI against clinician assessments and those using specialist diagnoses as a gold standard provide complementary evidence that might strengthen the case for AI's reliability in periodontal radiology (9,10).

Despite these promising results, our review identified several important limitations that must be addressed to translate this potential into clinical practice. Most evidence comes from retrospective or cross-sectional studies, with a notable lack of prospective validation in real-world clinical workflows, which limits understanding of true practical impact (12,16,19). Generalizability is a concern, as few models underwent external validation on datasets from different populations or imaging centers (8). There was also considerable heterogeneity in how outcomes were reported, with inconsistent use of key metrics, like AUC, hindering direct comparison and meta-analysis (9,15,19).

Finally, most developed models operate in isolation, relying solely on radiographic features without integration of crucial clinical parameters, such as probing depth. Future research should focus on creating clinically integrated tools, improving model interpretability for clinicians, and, most importantly, evaluating whether AI-assisted diagnosis improves actual patient outcomes, diagnostic confidence, or treatment planning efficiency.

This study has several limitations. First, the search strategy was limited to English-language publications and three electronic databases. Second, the inter-reviewer agreement was not formally measured, although discrepancies were resolved through consensus. Third, most included studies were retrospective or cross-sectional, with a lack of prospective clinical validation. Fourth, substantial heterogeneity in AI models (e.g. CNN, RCNN, U-Net, YOLO) and performance metrics (e.g. accuracy, sensitivity, specificity, precision, F1-score, AUC) precluded quantitative synthesis. Finally, external validation of the AI models was reported in only a limited number of studies, which may affect the generalizability of the results. The observed heterogeneity in performance across dataset sizes, model architectures, and validation approaches highlights the need for standardized reporting and external validation in future studies.

5. Conclusions

Implementing AI as a clinical adjunct may help standardize interpretation and improve diagnostic workflow efficiency. To advance toward clinical integration, the current, largely retrospective evidence must be strengthened by prospective, multi-center trials.

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Conflict of Interests

The authors have no conflict of interests to declare regarding this manuscript.

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