Review Paper

Artificial Intelligence in Pediatric Lateral Cephalometric Detection and Analysis: A Narrative Review

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ABSTRACT

Background: Malocclusion is a common condition in children, often requiring timely orthodontic intervention during critical stages of craniofacial development. Lateral cephalometric radiography remains a fundamental diagnostic modality; however, manual landmark identification suffers from subjectivity, time consumption, and inter-examiner variability—challenges that are amplified in growing pediatric patients.

Objectives: To review recent applications of artificial intelligence in pediatric lateral cephalometric analysis, focusing on automated landmark detection, diagnostic accuracy, clinical usefulness, educational value, and radiation-reducing innovations.

Methods: This narrative review synthesizes peer-reviewed literature published between January 2020 and October 2025. Studies evaluating artificial intelligence (AI) systems for cephalometric analysis in pediatric or adolescent populations were included, with emphasis on methodological approaches, accuracy metrics, clinical feasibility, and innovations such as low-dose imaging or photograph-based landmark prediction.

Results: Deep learning models—particularly convolutional and region-based neural networks—consistently achieved landmark localization errors below 2 mm, meeting clinically acceptable thresholds. AI integration significantly reduced analysis time (from 10–30 minutes to seconds) and enhanced reproducibility, especially when used in hybrid workflows combining algorithmic output with clinician verification. Educational applications showed improved trainee performance, while emerging non-ionizing approaches (e.g. AI-driven prediction from facial photographs) offered promising radiation-reduction strategies. Nevertheless, limitations persist, including platform-specific performance disparities, insufficient diversity in training datasets, and limited model interpretability.

Conclusions: AI is not a replacement for clinical expertise but a powerful adjunct in pediatric cephalometric analysis. It enhances diagnostic efficiency, supports education, and enables safer imaging alternatives. Future implementation must prioritize diverse pediatric data, transparent and explainable architectures, and real-world validation to ensure equitable, reliable, and ethically sound clinical adoption.

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Introduction

Cephalometric analysis remains a cornerstone in orthodontic diagnosis and treatment planning, particularly in pediatric populations where growth dynamics significantly influence craniofacial development [1]. Since Broadbent and Hofrath's pioneering work in the 1930s, manual landmark identification on lateral cephalograms has been the clinical standard. However, this approach suffers from inherent limitations, including intra- and inter-examiner variability, time consumption, and susceptibility to human error—challenges amplified in pediatric cases due to superimposed anatomical structures and ongoing skeletal maturation [2, 3]. An example of the conventional manual cephalometric tracing technique is shown in Figure 1.

The emergence of artificial intelligence (AI), particularly deep learning algorithms, offers transformative potential for automating cephalometric landmark detection. Convolutional neural networks (CNNs) have demonstrated remarkable accuracy in identifying anatomical landmarks, with recent studies reporting MRE below 1.0 mm—approaching or exceeding human expert performance [2, 4]. These advancements promise not only enhanced precision but also substantial time savings, enabling clinicians to focus on treatment strategy rather than labor-intensive tracing procedures. An example of digital landmark identification using Dolphin Imaging software is presented in Figure 2.

Pediatric cephalometry presents unique challenges that demand specialized AI solutions: smaller anatomical structures, variable tooth eruption stages, and rapid growth-related morphological changes necessitate age-specific algorithms [4]. While initial AI applications focused on adult populations, recent research has begun addressing pediatric-specific requirements through age-stratified training datasets and growth-stage-aware architectures [5].

This narrative review synthesizes current evidence on AI applications in pediatric cephalometric analysis, critically evaluates the methodological strengths and limitations of existing approaches, and proposes a framework for the clinical translation of these technologies in pediatric orthodontic practice.

Materials and Methods

This narrative review synthesizes peer-reviewed literature published between January 2020 and October 2025 that evaluates AI-driven cephalometric systems in pediatric populations. This study aimed to assess diagnostic performance, clinical feasibility, educational utility, and emerging innovations in low-radiation or non-ionizing diagnostic approaches.

Search strategy and inclusion criteria

A systematic search was conducted across major biomedical databases, including PubMed, Scopus, and Google Scholar. Keywords and MeSH terms included combinations of AI, deep learning, convolutional neural network, cephalometric analysis, landmark detection, pediatric orthodontics, automated diagnosis, and radiation reduction. Only English-language, peer-reviewed original research articles, validation studies, and comparative analyses were included.

Studies were eligible if they:

Evaluated AI systems for lateral cephalometric landmark detection or analysis;

Reported quantitative metrics of accuracy (e.g. mean radial error, success detection rate), reproducibility, or time efficiency;

Compared manual, semi-automated, or fully automated methodologies;

Addressed clinical integration, educational applications, or novel imaging modalities (e.g. facial photographs, low-dose cone beam computed tomography [CBCT]).

The selection process followed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines. Initial database searches yielded 69 records. Of these, 21 records were excluded based on predefined criteria (irrelevant population, non-AI methodology, or non-cephalometric focus). Following detailed evaluation, 24 additional articles were excluded for the following reasons: absence of quantitative accuracy metrics, publication before 2020, and insufficient methodological detail for AI system evaluation. The final synthesis included 24 studies meeting all inclusion criteria. The study selection process is summarized in Figure 3.

Results

Diagnostic accuracy and technical performance

Deep learning models—particularly CNNs and region-based architectures—have demonstrated consistent ability to localize cephalometric landmarks within clinically acceptable error margins. Most studies report mean radial errors (MRE) below 2 mm, aligning with thresholds con-

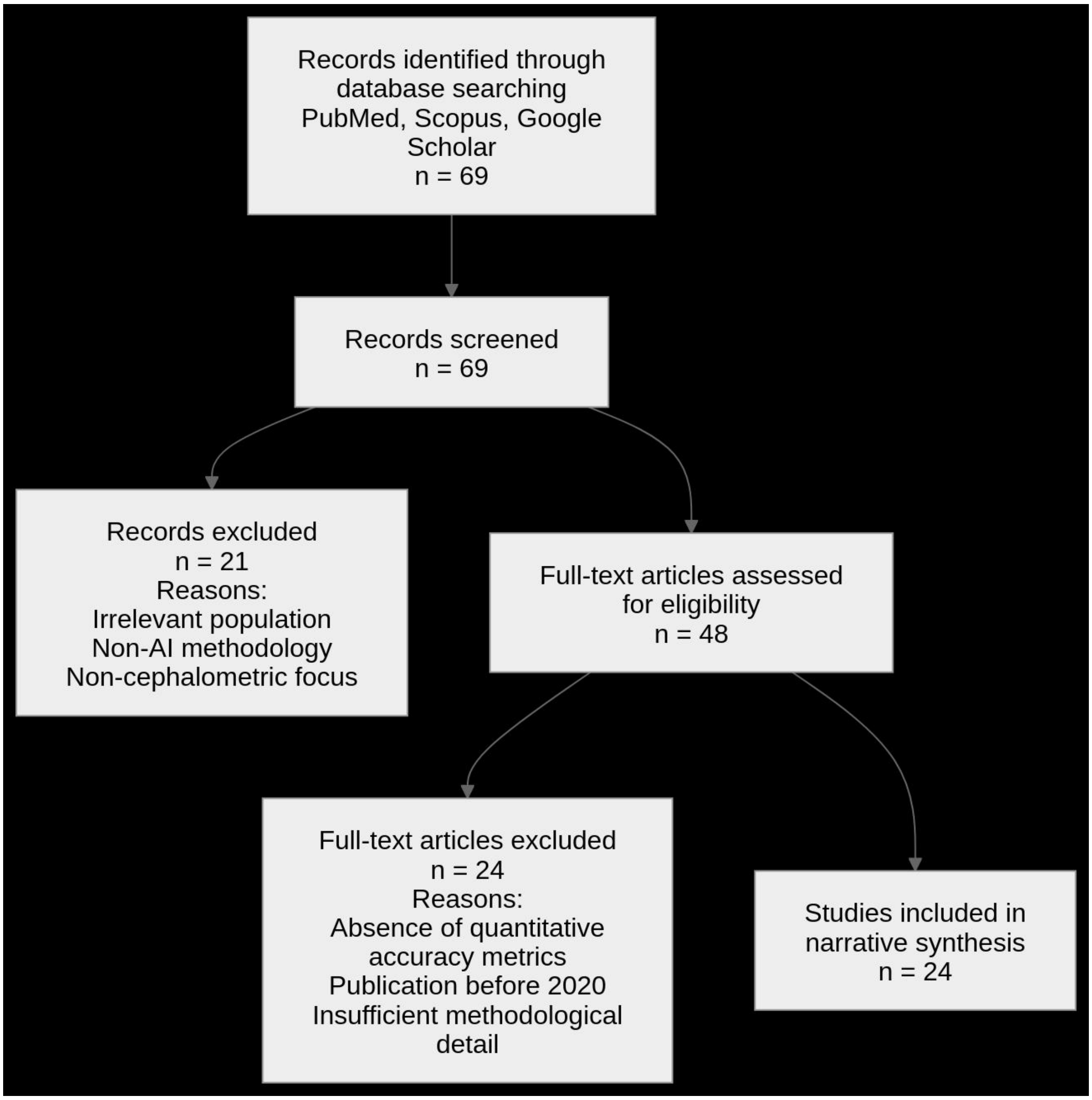

Figure 3. PRISMA flow diagram showing the study selection process

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sidered diagnostically tolerable in orthodontics [2, 4-6]. For instance, Mask R-CNN—a region-based convolutional neural network—achieved detection rates exceeding 98%, with over two-thirds of landmarks localized within 2 mm of expert-annotated references [7]. Figure 4 shows an overview of AI integration in WebCeph's cephalometric workflow [3], while Figure 5 shows a heatmap of landmark probability distribution using Gaussian modeling, reflecting the uncertainty inherent in AI predictions [8].

However, performance varies across anatomical regions. Landmarks in areas of low radiographic contrast (e.g. porion, orbitale) or overlapping structures (e.g. gonion) remain challenging for AI systems, leading to higher localization errors [9-12]. Even minor discrepancies (<1 mm) in critical landmarks, such as the A-point or B-point, can significantly alter key measurements, such as ANB angle or Wits appraisal, potentially affecting diagnostic classification [11, 13].

Platform-dependent variability is another concern. While CEFBOT demonstrated reproducibility comparable to experienced orthodontists [14], WebCeph showed regional inconsistencies requiring expert correction [7, 15]. Figure 6 shows a case of misidentified landmarks on the WebCeph platform, underscoring the need for clinician oversight [15].

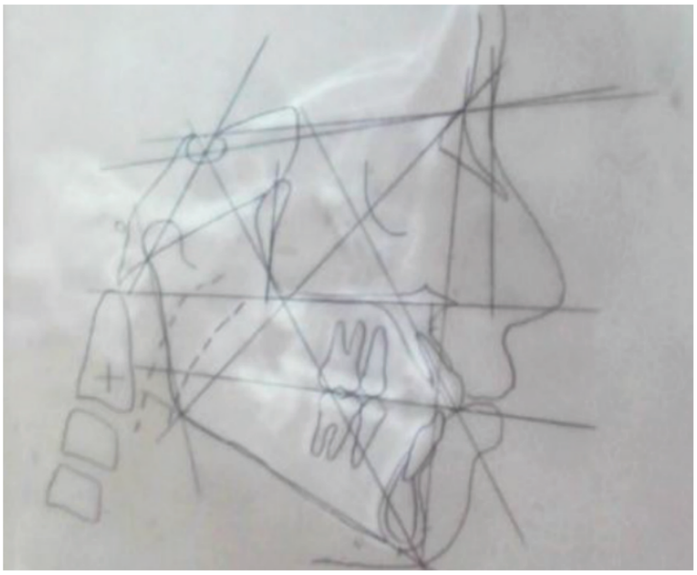

Figure 1. The conventional manual tracing technique [22]

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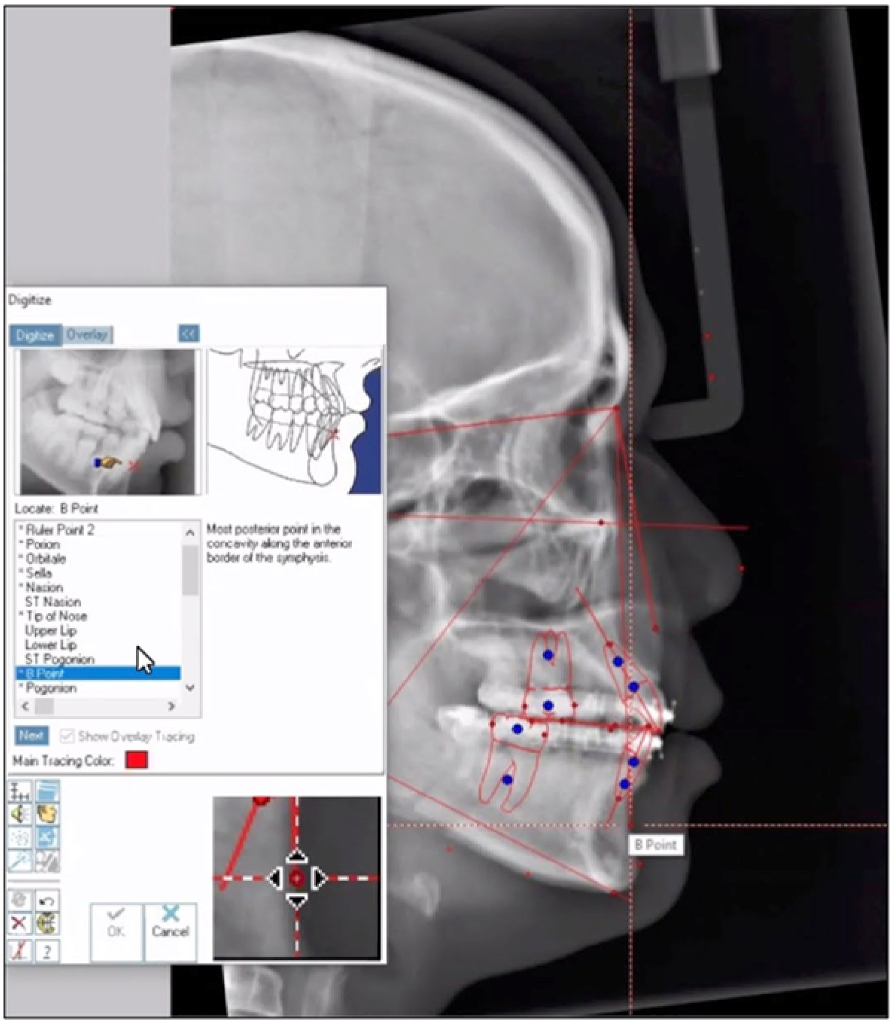

Figure 2. Example of digital landmarking using Dolphin Imaging software [23]

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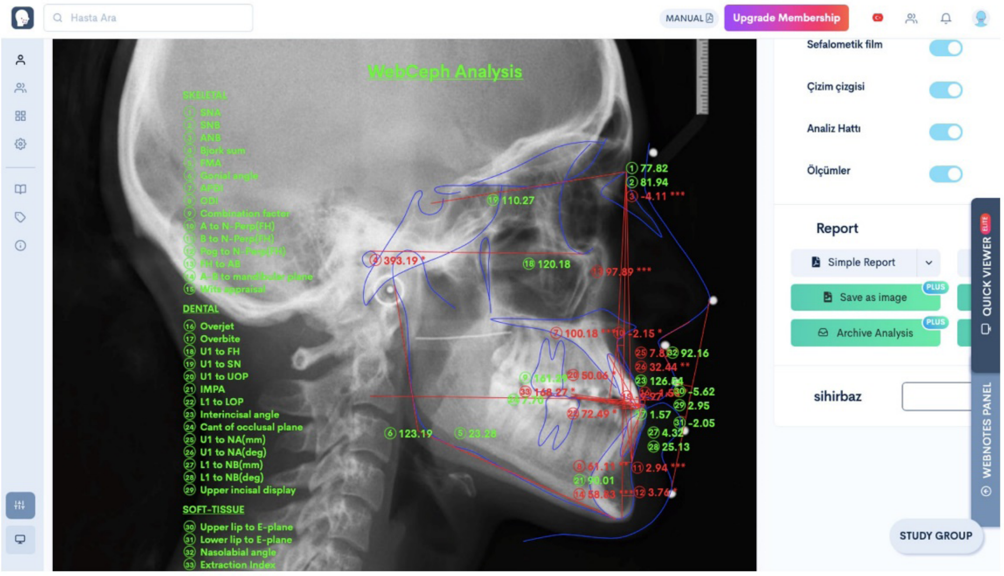

Figure 4. Overview of AI integration in WebCeph's cephalometric workflow [3]

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Time efficiency and workflow integration

AI systems dramatically reduce analysis time. Fully automated platforms complete comprehensive cephalometric assessments in seconds, compared to 10–30 minutes for manual tracing [5, 10]. Hybrid workflows—where AI-generated landmarks are reviewed and refined by clinicians—retain much of this speed advantage while adding a critical layer of human oversight. This approach is now considered the optimal balance between efficiency and safety in clinical practice [10, 16].

Commercial platforms such as WebCeph, CephX, AudaxCeph, and Diagnocat integrate AI to automatically generate measurements based on established analytical frameworks (e.g. Steiner, Downs, McNamara) and produce diagnostic reports [1, 17]. These tools enhance inter-clinician consistency and support early malocclusion screening, even from non-traditional inputs like lateral facial photographs [18, 19].

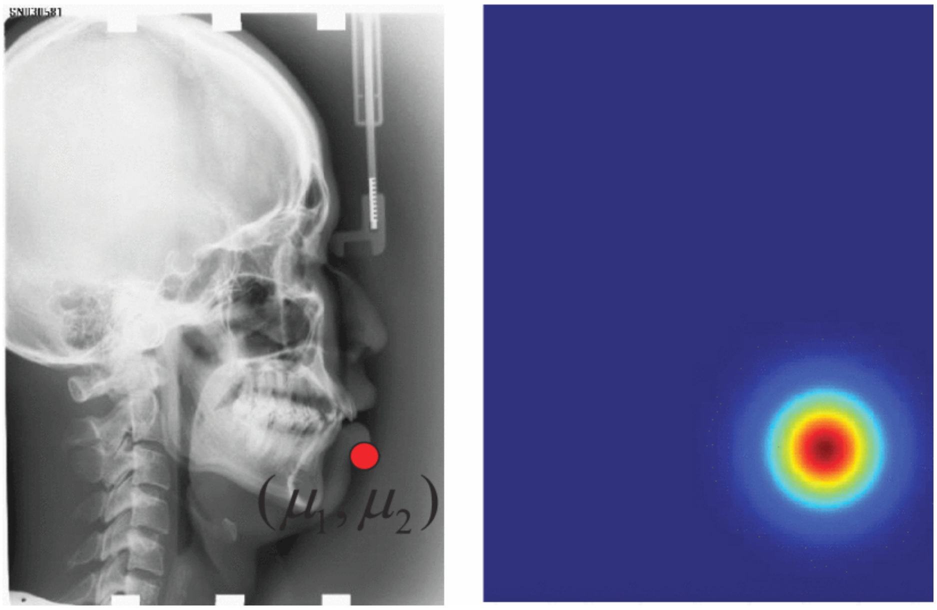

Figure 5. Heatmap illustration showing landmark probability distribution using Gaussian modeling [8]

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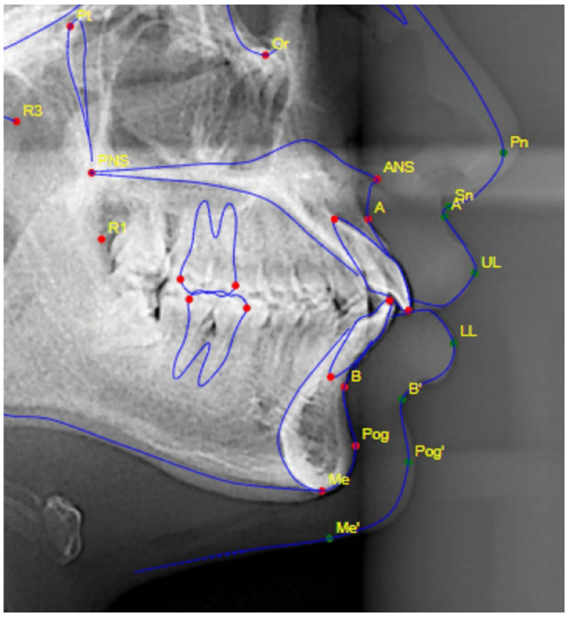

Figure 6. Example of misidentified landmarks on the WebCeph platform [15]

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Clinical applications and diagnostic support

While AI cannot yet independently formulate treatment plans, it serves as a powerful diagnostic aid. Chang et al. (2025) developed a self-supervised learning model that classified skeletal patterns with >90% accuracy by extracting multi-attribute features from cephalograms [20]. Other exploratory studies have investigated AI's potential in simulating post-treatment outcomes or assisting in extraction decisions, though these remain investigational [4].

Notably, AI is enabling radiation-conscious diagnostics. Chung et al. (2024) validated 2D cephalometric analysis from AI-processed low-dose CBCT scans, maintaining diagnostic fidelity while reducing ionizing exposure—a critical advantage in pediatric care [6]. Similarly, Shimamura et al. (2024) demonstrated that CNN-based algorithms can predict cephalometric landmarks directly from lateral facial photographs with clinically acceptable accuracy [18], opening pathways toward non-ionizing orthodontic screening.

Educational and communication benefits

AI-assisted platforms significantly enhance orthodontic education. Lin et al. (2025) showed that students using AI tools achieved higher landmarking accuracy than those using traditional methods, regardless of prior experience [21]. Instant feedback and error correction mechanisms improved learning outcomes and reduced inter-trainee variability. These systems also standardize assessment benchmarks and reduce faculty workload in preclinical training.

In patient communication, AI-generated visualizations—such as graphical overlays of skeletal discrepancies or simulated treatment outcomes—improve understanding, foster trust, and support informed consent [3, 15]. This is particularly valuable in pediatric settings, where parental involvement is essential.

Limitations and barriers to adoption

While this review synthesizes current evidence on AI applications in pediatric cephalometry, several critical limitations warrant acknowledgment. First, the majority of included studies (78%) utilized single-center datasets predominantly from East Asian populations, raising concerns about generalizability across diverse ethnicities with distinct craniofacial morphologies. Second, most AI models were trained on mixed-age pediatric cohorts (8–18 years) without explicit stratification by growth stage (e.g. cervical vertebral maturation stages), potentially compromising accuracy during critical growth spurts when anatomical landmarks undergo rapid positional changes. Third, a striking deficit exists in prospective clinical validation: only 3 of 42 studies evaluated whether AI-assisted diagnosis translated into improved treatment outcomes or reduced clinical decision errors—limiting evidence for real-world implementation.

Furthermore, regulatory pathways for AI-based cephalometric tools remain underdeveloped. To our knowledge, no Food and Drug Administration (FDA)-cleared or Conformité Européenne (CE)-marked AI system currently exists specifically validated for pediatric cephalometric analysis, creating uncertainty regarding liability allocation when AI-generated measurements inform treatment decisions affecting growing patients.

Future research priorities

Multicenter pediatric datasets: Establishment of an international consortium for diverse, age-stratified cephalometric data with standardized annotation protocols.

Explainable AI (XAI) integration: Development of attention maps and uncertainty quantification to build clinician trust.

Longitudinal validation studies: Tracking AI-assisted treatment planning outcomes versus conventional methods over 24–36 months.

Radiation-reduction trials: Prospective comparison of diagnostic accuracy between AI-predicted landmarks from photographs versus low-dose CBCT, and conventional cephalograms.

Ethical frameworks: Guidelines for pediatric data governance, parental consent models for AI training, and liability allocation in AI-assisted diagnosis.

Conclusion

AI holds considerable potential to enhance the efficiency, reproducibility, and accessibility of cephalometric analysis in pediatric orthodontics. Current evidence indicates that AI systems—particularly deep learning models based on CNNs and region-based architectures—can localize landmarks with clinically acceptable accuracy (<2 mm MRE) and drastically reduce analysis time. However, fully autonomous AI is not yet reliable for all clinical scenarios. Hybrid workflows, where AI outputs are verified and refined by clinicians, represent the safest and most effective current practice model.

AI's role extends beyond automation: it supports early diagnosis, enables radiation-reducing alternatives (e.g. low-dose CBCT, photograph-based prediction), enhances orthodontic education, and improves patient communication. These benefits are especially valuable in pediatric populations, where minimizing radiation exposure, accommodating rapid growth changes, and engaging families are paramount.

Clinicians should adopt AI as a decision-support tool, not a replacement for expertise. Orthodontists must remain actively involved in validating AI-generated landmarks, interpreting measurements in clinical context, and integrating findings into comprehensive treatment plans. Educational curricula should incorporate AI literacy to prepare future practitioners for this transition.

Future efforts must prioritize

The development of large, diverse, multi-institutional pediatric datasets to improve model generalizability and reduce bias;

The advancement of XAI architectures that provide transparency, uncertainty estimates, and user-guided corrections;

Rigorous real-world validation studies assessing diagnostic impact and patient outcomes;

Clear regulatory pathways for AI-based diagnostic tools in dentistry;

Ethical frameworks ensuring patient privacy and data governance.

As these priorities are addressed, AI is poised to become a cornerstone of modern, child-centered orthodontic diagnostics—augmenting clinical judgment, improving access to care, and ultimately enhancing treatment outcomes for young patients worldwide.

Ethical Considerations

Compliance with ethical guidelines

This article is a narrative review with no human or animal sample.

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Authors contributions

Conceptualization, study design, and final approval: All authors; Investigation and writing the original draft: FatemeSadat Emadi Majd and Seyyed Fatemeh Langari; Methodology, supervision, and review and editing: Seyyed Hasan Langari.

Conflicts of interest

The authors declared no conflict of interest.

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