Artificial Intelligence in Orthodontics: Current Applications and Future Directions — A Narrative Review.

Abstract

Background: Artificial intelligence (AI) has moved from a theoretical construct in computer science to an active clinical tool across dentistry, and orthodontics has emerged as one of its most receptive subspecialties.

Aim: To synthesise the published literature on AI applications across the major domains of orthodontic practice and to summarise their reported performance, benefits, and limitations. **Materials and Methods:** A narrative review of peer-reviewed literature indexed in PubMed, Google Scholar and Scopus was conducted, using combinations of the keywords “artificial intelligence”, “machine learning”, “deep learning”, “orthodontics”, “cephalometrics”, “CBCT”, “clear aligners”, “growth prediction” and “orthognathic surgery”. Findings were organised descriptively by clinical domain; no meta-analytic pooling was performed.

Results: Machine learning and deep learning algorithms are now used to trace cephalometric landmarks, analyse cone-beam computed tomography (CBCT) volumes, support extraction and treatment-planning decisions, monitor clear aligner therapy remotely, predict pubertal growth timing, plan orthognathic surgery, and forecast treatment outcomes in Class II and Class III malocclusion. Across these applications, AI-based systems frequently match or approach the performance of experienced clinicians while reducing time and inter-observer variability, though accuracy remains uneven for anatomically complex or poorly imaged landmarks, and most tools remain validated on limited, single-centre datasets.

Conclusion: AI is best understood, at its current stage of development, as an adjunct that augments orthodontic clinical judgement rather than a substitute for it. Realising its full potential will depend on larger validated datasets, transparent algorithms, and regulatory frameworks that keep pace with clinical adoption.

Keywords: Artificial intelligence; machine learning; deep learning; orthodontics; cephalometrics; clear aligners

1. Introduction

The idea of a machine that reasons like a human predates the computer itself, tracing back through Aristotelian syllogism and Ramon Llull's fourteenth-century Ars generalis ultima to Alan Turing's imitation game of 1950.[1–3] The term "artificial intelligence" was coined in 1955 and formalised the following year at the Dartmouth workshops organised by John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon, an event now regarded as the founding of AI as an academic discipline.[2] Medicine adopted these tools early, with Stanford's AI-in-Medicine programme and expert systems such as MYCIN and INTERNIST appearing in the early 1970s; dentistry's uptake has been more recent but is accelerating rapidly as digital imaging, intraoral scanning, and cloud computing generate the large datasets on which modern algorithms depend.[4]

Orthodontics is particularly well suited to AI adoption. Diagnosis and treatment planning depend heavily on quantifiable image-based data — cephalometric radiographs, CBCT volumes, digital models and photographs — and on decisions (extraction versus non-extraction, growth timing, appliance selection) that are amenable to pattern recognition. Conventional orthodontic diagnosis remains time-intensive, operator-dependent and subject to inter- and intra-examiner variability; AI-based systems promise a shift toward more reproducible, data-driven decision-making.[5] This review synthesises the peer-reviewed literature on AI applications spanning diagnostic imaging, treatment planning, clear aligner therapy, growth and outcome prediction, orthognathic surgery, and temporomandibular joint (TMJ) assessment, and considers the ethical and regulatory questions that accompany this technology's clinical integration.

2. Materials and Methods

A narrative literature review was conducted using the PubMed, Google Scholar and Scopus databases for articles published between January 1985 and August 2026. Search terms included combinations of “artificial intelligence”, “machine learning”, “deep learning”, “orthodontics”, “cephalometrics”, “CBCT”, “clear aligners”, “growth prediction”, “orthognathic surgery”, and “temporomandibular joint”. Peer-reviewed original research articles, systematic reviews and scoping reviews addressing AI applications in orthodontic diagnosis, treatment planning, or clinical monitoring were included. Non-peer-reviewed sources, conference abstracts without accompanying full text, and articles unavailable in English were excluded. Given the narrative design of this review, no formal risk-of-bias appraisal or meta-analytic synthesis was performed; findings are instead presented descriptively and organised by clinical domain, as summarised in Table 1.

Table 1. Summary of AI applications in orthodontics by clinical domain

Clinical domain	Representative AI technique	Representative source(s)	Reported outcome
Cephalometric landmark tracing	CNN-based automated tracing	Lee et al.[10]	>90% landmark identification success; 1–2 mm deviation for well-defined points
CBCT landmark detection	3-D CNN / hybrid active-shape models	Codari et al.[12]; Montufar et al.[15]	~2–3 mm mean error (landmark-dependent); up to 7 mm for porion
Extraction decision-making	ANN / multilayer perceptron	Kong et al.[18]	94% accuracy for extraction vs non-extraction
TMJ osteoarthritis diagnosis	Multisource ML (random forest, SVM, CNN)	Multisource biomarker models[23–24]	~0.82 accuracy for early-stage detection
Clear aligner remote monitoring	Deep-learning image analysis (AIRM)	Hansa et al.[28]; Roisin et al.[29]	25–33% reduction in required visits

Clinical domain	Representative AI technique	Representative source(s)	Reported outcome
Growth / CVM staging	Interactive deep learning (ARNet-v2)	Kim & Song[34]	67% reduction in prediction failures vs prior systems
Orthognathic surgery planning	AI-assisted soft-tissue prediction	Scoping reports[35–36]	Improved reproducibility of outcome visualisation (qualitative)
Class II outcome prediction	U-Net-based CNN	Cephalometric prediction study[37]	<1.0 mm error at A-point/ANS; >2 mm at chin region
Class III prognosis	Network analysis / fuzzy clustering	Auconi et al.[38]	Predicts RME and facemask therapy success

3. Fundamentals of Machine Learning and Deep Learning

Machine learning (ML) refers to algorithms that improve their performance on a task through exposure to data rather than explicit programming. Within ML, artificial neural networks (ANNs) loosely model biological neurons across input, hidden, and output layers, and are the basis of most orthodontic AI applications reported to date.[6] Convolutional neural networks (CNNs) — the dominant architecture for image-based tasks — use convolutional and pooling layers to automatically extract edges, textures and anatomical contours without manual feature engineering, and underlie architectures such as U-Net, ResNet and DenseNet that recur throughout the orthodontic literature.[7] These networks support four broad image-analysis tasks relevant to orthodontics: classification (e.g., syndromic versus non-syndromic facial phenotypes), segmentation (e.g., cephalometric landmarks, the mandible, or the airway), object detection (e.g., impacted canines on panoramic radiographs), and image reconstruction or enhancement (e.g., noise reduction in low-dose CT).[7] A recurring theme across the studies reviewed below is that model performance depends heavily on training-dataset size and quality, and that reported accuracies — often derived from single-institution samples — do not automatically generalise across populations, imaging protocols, or equipment.

4. AI in Cephalometric and CBCT Analysis

Cephalometric analysis, introduced by Broadbent in 1931, remains central to orthodontic diagnosis but is time-consuming and prone to inter- and intra-examiner variability in manual landmark tracing.[8] Automated landmark detection was first explored by Levy-Mandel et al. in 1985 and has since been revisited using progressively more sophisticated architectures.[9] Lee et al. reported a deep CNN-based tracing system achieving over 90% success in landmark differential diagnosis, broadly comparable to experienced orthodontists, and platforms such as Dolphin Imaging, CephX, WebCeph and OneCeph now offer AI-assisted tracing with manual override.[10] Reported deviations from manual tracing typically fall within 1–2 mm for well-defined points, but error rates of 2–10% persist for structurally ambiguous landmarks such as orbitale, condylion and gonion, where anatomical overlap or poor image contrast limits automated detection (Figure 1).[10]

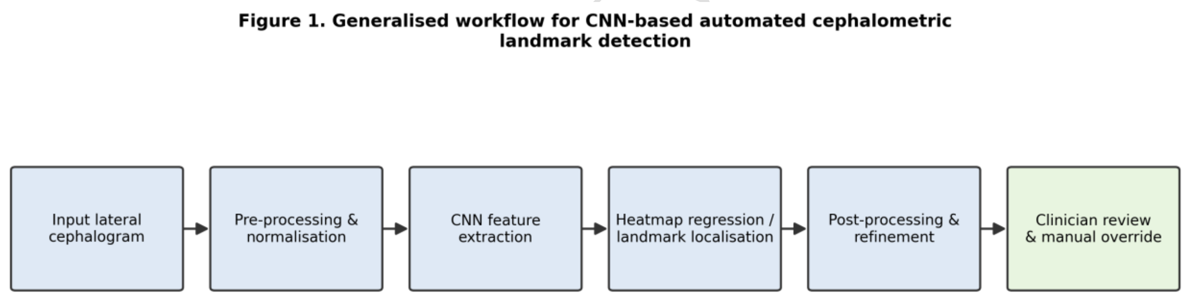

Figure 1. Generalised workflow for CNN-based automated cephalometric landmark detection, from image input through clinician verification.

Extending this work into three dimensions has proved harder. Automated CBCT landmark-detection methods — including Gupta et al.'s head-searching algorithm, Codari et al.'s non-rigid registration approach, and Makram and Kamel's Reeb-graph method — have reported mean localisation errors ranging from roughly 2 mm to over 3 mm, with accuracy varying widely by landmark; points such as Sella, PNS and porion have proved particularly resistant to automation, with porion errors reported as high as 7 mm in some series.[11–14] Hybrid approaches combining active shape models with knowledge-based local search have modestly improved on these figures, and three-dimensional CNN architectures — which capture both spatial and volumetric information from CBCT voxel data rather than 2-D pixel data — represent the current frontier, including deep geodesic-learning pipelines combining U-Net-based mandible segmentation with landmark identification via long short-term memory networks.[15] Despite this progress, the authors of these studies consistently note that current CBCT landmarking accuracy remains insufficient for unsupervised clinical deployment and requires further validation before routine use.

5. AI in Diagnosis and Treatment Planning

Beyond imaging, AI has been applied directly to orthodontic decision-making, most notably the extraction-versus-non-extraction decision. Xie et al.'s expert system using error-backpropagation ANN achieved roughly 80% accuracy in identifying the need for extraction in adolescent patients, while Jung et al. reported 84% accuracy in predicting specific extraction patterns.[16–17] Kong et al.'s multilayer-perceptron model extended this to a full decision cascade — extraction versus non-extraction (94% accuracy), extraction pattern (84.2%), and anchorage pattern (92.8%) — with crowding, upper-arch dimension, ANB angle and curve of Spee identified as the most influential predictors (Table 2), leading the authors to suggest such tools could guide less experienced clinicians.[18]

Table 2. Reported performance of AI models in orthodontic extraction decision-making

Study	Algorithm	Predictive task	Reported accuracy
Xie et al.[16]	ANN (error-backpropagation)	Extraction vs non-extraction	80%
Jung et al.[17]	Artificial neural network	Extraction pattern prediction	84%
Kong et al.[18]	Multilayer perceptron	Extraction vs non-extraction	94%
Kong et al.[18]	Multilayer perceptron	Extraction pattern	84.2%
Kong et al.[18]	Multilayer perceptron	Anchorage pattern	92.8%

Related applications include facial-analysis tools such as Face2Gene, which compares a patient's facial image against large syndromic databases and has reportedly outperformed clinicians in identifying certain craniofacial genetic syndromes, and machine-learning-assisted prediction of impacted canine eruption from panoramic and cephalometric measurements, where random-forest models achieved approximately 83% accuracy.[19–20] Soft-tissue outcome prediction has also benefited: ANN models predicting post-treatment lip curvature and Peer Assessment Rating (PAR) scores have outperformed conventional linear regression, correctly predicting final PAR scores 94% of the time versus 82% for regression-based methods.[21]

These figures should be read cautiously. Most studies report accuracy on retrospective, single-centre cohorts without external validation, and “accuracy” is defined inconsistently across papers (some measure agreement with a single expert rater, others with consensus panels). The consistent finding, nonetheless, is that neural-network models tend to outperform classical statistical approaches such as linear regression when the decision space involves many interacting clinical variables — precisely the situation orthodontists face in real practice.

6. AI in Temporomandibular Joint Disease

Temporomandibular joint osteoarthritis (TMJ-OA) is diagnostically challenging because of its multifactorial aetiology, requiring integration of clinical, imaging (CBCT, MRI) and, increasingly, molecular biomarker data.[22] AI-based decision-support systems attempt to combine these heterogeneous data sources: radiomics extraction from CBCT can characterise mandibular condyle trabecular bone and shape features imperceptible to visual inspection, while machine-learning classifiers (random forest, support vector machines, gradient-boosted trees, and CNN-based segmentation networks such as U-Net) group patients by radiomic similarity.[23] Ribera et al.'s Shape Variation Analyzer used mesh-derived features (curvature, shape index, heat-kernel signatures) to classify condylar degeneration against clinician-labelled training sets, and multisource models integrating clinical, imaging and biomarker data have reported accuracies around 0.82 for detecting early-stage TMJ-OA — notably outperforming models built on any single feature category, which underscores the value of multimodal data fusion in this domain.[24] Automated segmentation tools such as MJSeg reduce the substantial manual workload of 3-D condylar segmentation from CBCT, and AI-assisted reading of panoramic radiographs has been proposed to reduce misdiagnosis of TMJ osteoarthritic changes in settings without ready access to a specialist reader.[25] As with cephalometric CBCT work, these tools remain in early validation stages and depend on carefully standardised, multicentre imaging protocols to achieve generalisable performance.

7. AI in Personalized Treatment Planning and Clear Aligner Therapy

Clear aligner therapy has become one of the most AI-intensive areas of orthodontic practice. Treatment-planning platforms use algorithms to analyse digital scans, stage tooth movement, and optimise force application, while predictive models estimate the likelihood of requiring mid-course refinement, reported at around 70% accuracy in some series.[26] Tooth segmentation from intraoral scans — previously reliant on threshold-based algorithms — has been shown to improve when AI-based methods are substituted, streamlining the digital workflow that underlies most of the more than sixty commercial aligner systems now available worldwide (Table 3).[27]

Table 3. Selected commercially available AI-enabled clear aligner treatment-planning platforms

Clear aligner system	Planning software	Company	Origin
Invisalign®	ClinCheck Pro®	Align Technology	Arizona, USA
Spark Clear Aligners	Approver™	Ormco	California, USA
SureSmile® Aligners	SureSmile Simulator	Dentsply Sirona	Bensheim, Germany
3Shape Clear Aligner	3Shape Clear Aligner Studio	3Shape	Copenhagen, Denmark
Blue Sky Plan	BlueSkyPlan Ortho Module	BlueSkyBio	Illinois, USA
uLab	uDesign® 7	uLab Systems, Inc.	California, USA
Angel Aligner	iOrtho	Angelalign Technology Inc	Shanghai, China

Clear aligner system	Planning software	Company	Origin
ArchForm®	ArchForm	ArchForm Inc.	California, USA
OrthoFX	FXPlan	OrthoFX	Texas, USA

The most extensively studied application is AI-driven remote monitoring (AIRM), exemplified by systems such as Dental Monitoring, in which patients submit smartphone images that a deep-learning pipeline analyses for roughly 180 clinical metrics, including attachment loss, decalcification, gingival inflammation, aligner fit, and tracking accuracy (Figure 2). Hansa et al. reported that AIRM reduced required Invisalign appointments by approximately 25% compared with conventional monitoring, and Roisin et al. similarly found a reduction of about 3.5 visits (33%) per patient with no clinically significant difference in tooth-tracking accuracy or overall treatment duration.[28–29]

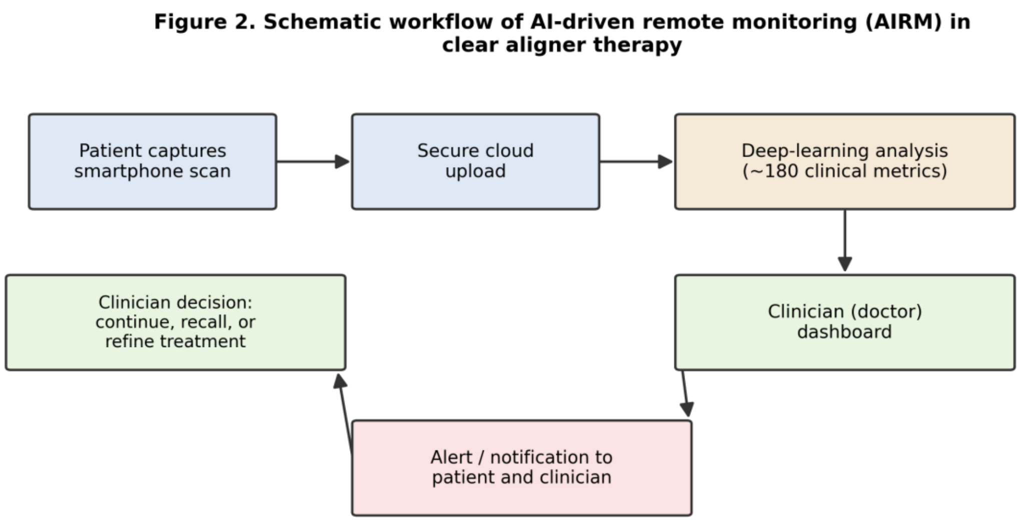

Figure 2. Schematic workflow of AI-driven remote monitoring (AIRM) in clear aligner therapy.

Kuriakose et al. found that AIRM-based assessment of rapid maxillary expansion correlated well with in-person clinical evaluation, suggesting expansion protocols may also be safely monitored remotely.[30] Reported clinical use-cases include early detection of aligner fracture, missing attachments, loss of tracking, arch-wire passivity in fixed appliances, and post-retention relapse — functions that shift some monitoring burden from scheduled in-person visits to continuous, asynchronous surveillance, a capability whose value was particularly evident during the COVID-19 pandemic.[28] The consistent limitation across this literature is that AIRM reduces, but does not eliminate, the need for clinical examination, and its accuracy for subtler findings (e.g., early root resorption, periodontal changes) is less well established than for the mechanical parameters it was originally designed to track.

8. AI in Growth Prediction

Timing treatment to a patient's growth peak is central to orthodontic and orthopaedic decision-making, and has traditionally relied on hand-wrist radiographs or cervical vertebral maturation (CVM) staging, both requiring manual annotation and subject to inter-observer variability.[31] Deep-learning approaches to CVM staging have proliferated: Kök et al. and Amasya et al. compared multiple machine-learning classifiers for determining cervical vertebral maturation stage from lateral cephalograms, reporting accuracies that, in several architectures, approached or exceeded conventional manual staging.[32–33] The most recent advance in this domain is the Attend-and-Refine Network (ARNet-v2), described by Kim and Song in 2025 (Figure 3), an interactive deep-learning model that identifies cervical vertebral landmarks from a single lateral cephalogram and propagates a single manual correction across related anatomical points. Trained and validated on more than 5,700 radiographs across four public datasets, ARNet-v2 reduced prediction failures by up to 67% and halved the number of manual corrections required compared with existing systems, while offering the clinical advantage of estimating pubertal growth peak without an additional hand-wrist radiograph — reducing radiation exposure and cost in paediatric patients.[34]

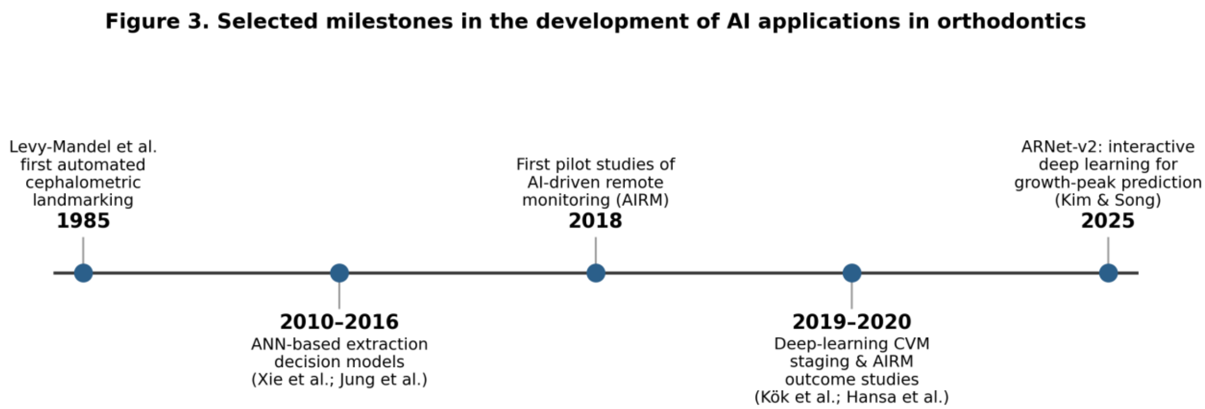

Figure 3. Selected milestones in the development of AI applications in orthodontics.

Such tools illustrate a broader trend in this literature: growth-prediction models are moving from single-radiograph classification tasks toward interactive systems designed to minimise clinician correction time while preserving expert oversight, rather than aiming for fully autonomous prediction.

9. AI in Orthognathic Surgery Planning

Orthognathic surgical planning is inherently multidisciplinary and technique-sensitive, and AI has been proposed as a means of reducing operator bias in the interpretation of clinical and radiographic data.[35] Reported applications include AI-assisted prediction of post-surgical facial soft-tissue change, which may improve patient communication and informed consent by providing more realistic visualisation of anticipated outcomes, and AI-supported design of patient-specific bone implants and surgical guides, intended to shorten operative time and improve precision.[36] Fully AI-integrated digital workflows — combining automated diagnosis, virtual surgical planning and soft-tissue outcome simulation — have been proposed as the logical endpoint of this trajectory, though most published evidence to date addresses individual components of the workflow (e.g., landmark identification or soft-tissue prediction) rather than validated end-to-end systems.[36]

10. AI in Predicting Treatment Outcomes: Class II and Class III Malocclusion

Predicting non-extraction treatment outcomes in Class II malocclusion has been addressed using CNN-based models trained on paired pre- and post-treatment lateral cephalograms. In one representative study of 284 patients treated by maxillary molar distalisation with a modified C-palatal plate, a U-Net-based deep-learning model predicted post-treatment hard- and soft-tissue landmark positions with prediction errors below 1.0 mm for the A-point, anterior nasal spine, and perinasal soft-tissue landmarks, though errors exceeded 2 mm at the chin region (soft-tissue pogonion and menton), reflecting the biomechanical complexity of mandibular response to molar distalisation.[37]

Class III prognosis has been approached from a different angle, using network-analysis and fuzzy-clustering methods to model the craniofacial skeleton as an interconnected biological system rather than a set of independent cephalometric variables. Auconi et al. found that patients with more densely interconnected craniofacial "modules" (hyperdivergent and hypermandibular patterns) had significantly higher rates of unsuccessful outcomes following rapid maxillary expansion and facemask therapy than patients with a balanced pattern, and that pre-treatment fuzzy-cluster membership could be used to predict treatment success.[38] Machine-learning feature-selection techniques applied to longitudinal cephalometric data from Class III cohorts address the "curse of dimensionality" inherent to growth prediction — the tendency of classical statistical models to lose precision as the number of candidate predictors grows — by identifying the smaller subset of skeletal variables that carries most of the predictive signal.[39] Collectively, these studies suggest that both direct image-based prediction and more abstract network-based modelling of craniofacial growth can add prognostic value beyond conventional cephalometric analysis, though both approaches remain confined to research settings pending larger prospective validation.

11. Ethical, Legal and Regulatory Considerations

The clinical promise of AI in orthodontics is accompanied by unresolved ethical and regulatory questions. Core bioethical principles map onto specific risks: patient autonomy requires transparent disclosure when AI contributes to diagnosis or planning; beneficence and non-maleficence require that predictive errors do not translate into patient harm; justice requires that training datasets do not encode demographic or ethnic bias that could degrade performance in under-represented populations; and accountability requires that the treating clinician, not the algorithm, remains legally and professionally responsible for treatment decisions.[40] Remote-monitoring technologies raise a further, more specific concern: reduced physical examination may risk missing pathology (periodontal disease, root resorption, TMJ changes) that a longer-interval in-person recall would have caught, requiring clinicians to actively define what AIRM should not be relied upon to detect. Regulatory frameworks for AI-based medical devices remain underdeveloped globally, and the literature reviewed here calls for standardised validation protocols, clinical-trial-level evidence, and formal regulatory approval — for example through bodies such as the U.S. Food and Drug Administration — before widescale clinical deployment, cautioning that premature adoption without such safeguards risks patient safety.[40]

12. Future Directions

The trajectory of this literature points toward integration rather than isolated tools: combining three-dimensional imaging, intraoral scanning, remote-monitoring data and, potentially, genomic information within unified predictive platforms. Anticipated developments include AI-guided robotics for tasks such as bracket placement and wire bending, on-demand 3-D printing of AI-optimised appliances, expanded tele-orthodontic screening for underserved and rural populations, and AI-based patient-education tools that visualise likely treatment outcomes to support informed consent.[41] Orthodontic education is also expected to be affected, with simulation-based training and adaptive digital-literacy curricula proposed to prepare postgraduate trainees to critically evaluate — rather than passively accept — the outputs of clinical AI tools.

13. Conclusion

Across diagnostic imaging, treatment planning, clear aligner monitoring, growth assessment, orthognathic surgery and outcome prediction, AI-based methods consistently demonstrate the capacity to match or approach expert-level performance while reducing time and inter-observer variability. However, accuracy remains uneven across anatomical regions and clinical tasks, most supporting evidence derives from retrospective single-centre datasets without external validation, and unresolved ethical, legal and regulatory questions — data privacy, algorithmic bias, and clinical accountability foremost among them — temper the pace at which these tools should be adopted into routine practice. The weight of the evidence reviewed here supports a view of AI as an adjunct that augments, rather than replaces, orthodontic clinical judgement: the orthodontists best positioned for the future are not those who defer to algorithmic output, but those who understand its evidentiary basis well enough to use it critically.

Conflict of Interest

The authors declare no conflict of interest.

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