REVIEW ARTICLE

Limitations and Pitfalls of Artificial Intelligence in Orthodontics: A Narrative Review

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Abstract

Artificial intelligence (AI) is increasingly integrated into orthodontics, supporting tasks ranging from cephalometric landmark detection to treatment planning and remote monitoring. Evidence from recent literature shows consistent progress in diagnostic accuracy and workflow efficiency; however, its clinical impact remains dependent on validation, dataset quality, and regulatory clearance. Current applications demonstrate benefits in automated image analysis, multimodal data interpretation, and decision-support systems, yet real-world limitations persist. A major concern is restricted generalizability, as most models are trained on unicentric or homogeneous datasets, which raises risks of algorithmic bias and reduced reliability in complex or diverse clinical scenarios. Furthermore, ethical and legal factors, such as accountability, data privacy, and lack of standardized evaluation protocols, continue to limit large-scale adoption. Only a small proportion of AI tools have reached regulatory approval, underscoring the gap between experimental success and clinical maturity. This review synthesizes existing evidence, outlines key challenges, and highlights future directions, emphasizing the need for multicenter datasets, explainable AI systems, and structured regulatory frameworks to ensure safe and effective implementation in orthodontic practice.

Keywords: Artificial intelligence, Cephalometric analysis, Deep learning, Limitations, Machine learning, Narrative review, Orthodontics.

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Introduction

Artificial intelligence (AI) has emerged as a transformative force in contemporary orthodontics, with applications spanning automated cephalometric landmark detection, treatment planning, growth assessment, and digital workflow optimization.[1–3] Machine learning and deep learning frameworks, particularly convolutional neural networks (CNNs), now enable rapid, consistent analysis of radiographic and three-dimensional imaging data, augmenting diagnostic efficiency across a range of clinical tasks.[4,5] Published literature documents steady advances in model accuracy for cephalometric tracing, malocclusion classification, extraction decision-support, and orthognathic surgery planning, establishing AI as a promising adjunct in evidence-based orthodontic care.[1,2]

Despite these advances, critical lacunae remain that limit the safe and effective translation of AI from research settings to routine clinical practice. Most AI models in orthodontics are trained on unicentric, ethnically homogeneous, or inadequately annotated datasets, compromising their generalizability across diverse patient populations.[3,4] Biological individuality, including growth variability, periodontal response, and facial esthetic considerations, cannot be reliably captured by current algorithmic frameworks.[5,6] Furthermore, ethical and regulatory deficiencies, including ambiguous accountability for AI-generated errors, opaque "black-box" decision-making, and the limited number of clinically validated, regulatory-approved systems, represent substantive barriers to widespread adoption.[7,8]

This narrative review addresses the existing gap between AI's reported research performance and its real-world clinical applicability in orthodontics. The aim of this review is to systematically examine, synthesize, and critically evaluate the current limitations, pitfalls, and barriers associated with AI implementation in orthodontic diagnosis and treatment planning. The specific objectives are to: (1) identify technical limitations related to data quality, model architecture, and generalizability; (2) evaluate clinical constraints, including the inability to replicate adaptive human judgment; (3) assess ethical, legal, and regulatory challenges; and (4) outline evidence-based directions for future development and safer clinical integration of AI in orthodontics.

Methods

This study was designed as a narrative review. A comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, Web of Science, Google Scholar, and the Cochrane Library from inception to December 2024. Search terms used individually and in combination included "artificial intelligence in orthodontics," "machine learning orthodontics," "deep learning orthodontics," "convolutional neural network cephalometry," "AI limitations dentistry," "automated cephalometric analysis," and "algorithmic bias dental AI." Boolean operators (AND, OR) were used to refine search combinations.

Articles were included if they: (1) were published in peer-reviewed journals or established academic texts; (2) addressed AI,

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machine learning, or deep learning applications in orthodontics or related dental disciplines; (3) reported on technical performance, clinical utility, limitations, or ethical considerations of AI systems; and (4) were available in English. Studies were excluded if they were conference abstracts without full text or if they focused exclusively on AI in nondental medical fields with no orthodontic relevance. Following screening of titles and abstracts, full-text articles were retrieved and assessed for eligibility. Reference lists were also manually reviewed for additional relevant sources. Data extraction and thematic synthesis were performed narratively, grouping findings according to the following domains: (1) neural network architecture and data processing; (2) digital data management; (3) clinical monitoring and oversight; (4) treatment need assessment; (5) growth and developmental staging; (6) cephalometric analysis; (7) extraction decision-making; (8) orthognathic surgery planning; and (9) ethical, regulatory, and training considerations.

Results

A total of 45 sources were included in this narrative review following title, abstract, and full-text screening. The included literature comprised 28 original research articles (including experimental and observational studies evaluating AI model performance), nine systematic reviews or meta-analyses, five textbook chapters or reference texts, and three technical reports or consensus documents. Publication dates ranged from 1931 to 2024, with the majority (n = 36, 80%) published after 2015, reflecting the acceleration of AI research in orthodontics over the past decade. Thematic synthesis across the included sources consistently identified both the clinical utility and the inherent limitations of AI-based applications in orthodontics, organized across nine functional domains as described in the Methods section.[9–14]

Studies on neural network architectures demonstrated that deep learning models, including CNNs and generative adversarial networks (GANs), are capable of processing radiographic and three-dimensional imaging data with notable efficiency. However, model performance was consistently found to be contingent on the size, diversity, and annotation quality of training datasets. Insufficient or poorly labeled data were associated with unstable outputs and elevated error rates.[15,16]

In the domain of digital data management, the literature revealed considerable heterogeneity in dental record systems, with variations in formatting, completeness, and imaging standards limiting cross-institutional applicability. The increasing migration to cloud-based storage was identified as a source of concern regarding data security, confidentiality, and regulatory compliance.[17–25]

Regarding clinical monitoring and human oversight, reviewed studies emphasized that AI systems are unable to replicate the adaptive clinical judgment required during multi-year orthodontic treatment. Risks related to algorithm drift, undetected error accumulation, and absence of real-time situational awareness were reported across multiple studies.[26–35] Treatment need assessment models demonstrated progress but showed significant variability in borderline case classification due to interclinician diagnostic disagreement.[36–38]

Automated cephalometric systems based on CNN architectures achieved moderate-to-high landmark detection accuracy under controlled conditions; however, performance declined for anatomically ambiguous or overlapping structures, including the posterior nasal spine and soft-tissue landmarks.[27,39,31] Growth staging models utilizing cervical vertebral maturation indices showed moderate diagnostic accuracy but were prone to misclassification during transitional developmental phases.[39–43]

Extraction decision-support models showed concordance with expert opinion in straightforward cases but performed inconsistently when esthetic, periodontal, and patient-specific variables were introduced.[10–12] AI-assisted orthognathic planning tools demonstrated predictive value but lacked universal applicability due to interethnic variation in facial norms and the absence of standardized clinical benchmarks.[41–43] Ethical and regulatory analysis across the reviewed literature identified accountability gaps, black-box transparency issues, and limited regulatory approval as persistent barriers to large-scale clinical implementation.[44,45]

Discussion

The findings of this narrative review, synthesized from 45 sources spanning nearly a century of orthodontic and computational research, collectively demonstrate that while AI represents a genuine advance in clinical orthodontics, its current limitations are substantial and multidimensional. The evidence reviewed reveals a persistent and concerning gap between AI's reported performance in controlled experimental settings and its reliability in diverse, real-world clinical environments. This gap is not attributable to any single deficiency; rather, it reflects systemic challenges across data infrastructure, model design, clinical integration, and regulatory governance. Critically, much of the published literature evaluating AI in orthodontics suffers from methodological limitations of its own, including small sample sizes, unicentric data, lack of independent validation cohorts, and heterogeneous outcome measures, which further complicates confident clinical translation. The following subsections critically examine the findings across each thematic domain.

Neural Network Architecture and Information Processing

Artificial neural networks function as computational models inspired by neural signaling in the human brain, transmitting input through sequential layers to produce predictive clinical outputs.[1–5] Deep-learning variants improve analytical capability with multilayered processing, while convolutional systems are frequently used to evaluate radiographs, CBCT scans, and three-dimensional datasets for orthodontic assessment.[6–9] Generative architectures replicate dataset patterns to produce realistic diagnostic samples, supporting image synthesis and case simulation.[10,11] Neuron "weights" continuously adapt throughout model training, strengthening associations between clinical variables, such as dental alignment or occlusal discrepancies, and predictive outcomes.[12–14] Performance reliability depends heavily on dataset quality; insufficient volume or poor annotation leads to unstable outputs and increased error rates.[15,16] Critically, the field currently lacks a standardized benchmark dataset against which competing architectures can be objectively compared, making interstudy performance comparisons unreliable. The predominance of supervised learning approaches also means that models are inherently constrained by the quality and representativeness of their labeled training data, a significant limitation in a specialty where expert annotation is time-intensive and subject to interclinician variability.

Digital Information Management and Data Reliability

AI in orthodontics requires structured, standardized, and clinically validated digital records; however, most dental data systems vary significantly in formatting, completeness, and radiographic consistency.[17–20] Missing diagnostic information, irregular imaging protocols, and unverified case histories disrupt machine-learning performance and hinder cross-clinic applicability.[21,22] Expanding digital storage needs have prompted a shift toward cloud-based platforms, raising concerns regarding security, data ownership, confidentiality, and regulatory monitoring.[23–25] Without harmonized data standards, interoperability and benchmarking remain limited.[26] This is a particularly critical finding because data infrastructure is a prerequisite for all AI development, yet it receives comparatively little attention in the published orthodontic AI literature. The absence of shared, curated, multicentric orthodontic datasets is perhaps the single greatest structural obstacle to developing generalizable AI models. Until institutional and regulatory frameworks mandate interoperable data standards, each AI tool will remain essentially siloed, limiting scalability and independent validation.

Clinical Monitoring, Human Oversight, and Patient Well-being

While AI programs automate landmark tracing, measurements, and reporting, they cannot replace clinical examination or judgment.[27,28] Orthodontic treatment spans several years and requires adaptation to growth, biological response, and biomechanical changes that automated systems cannot fully predict.[29–31] Algorithm drift, data outliers, and unmonitored error accumulation present safety risks when systems are not continuously audited.[32,33] Ethical limitations also arise due to lack of empathy, professional accountability, and real-time situational awareness, which reinforces that AI should assist, but not replace, human oversight.[34,35] The concept of algorithm drift deserves particular attention in orthodontics, where treatment durations of 2–3 years mean that a model trained on historical data may progressively diverge from current clinical realities. No reviewed study addressed longitudinal model monitoring or described mechanisms for updating deployed systems, representing a notable gap in the safety literature. Furthermore, the emotional and motivational dimensions of orthodontic care, patient compliance, anxiety management, and shared decision-making, lie entirely outside the computational domain, reinforcing the irreplaceable role of the trained clinician.

Assessment of Treatment Need and Diagnostic Justification

Machine-learning models designed to evaluate treatment need have shown progress, but borderline cases remain problematic due to inconsistent diagnostic agreement among clinicians.[36–38] Variability between examiners influences training data, leading to algorithmic outcomes that may not align with clinical expectations.[39] AI-generated suggestions should therefore be interpreted as advisory tools rather than definitive treatment instructions.[40] Critically, if training labels are derived from clinicians who disagree with each other, then the model is, in effect, learning an averaged or dominant opinion rather than an objective ground truth. This has profound implications for borderline treatment decisions, where the margin between treating and not treating has long-term implications for skeletal growth, dental health, and patient quality of life. Current AI tools do not communicate the uncertainty inherent in their outputs, which poses a significant risk of false precision in clinical decision-making.

Evaluating Developmental Maturity and Growth Interpretation

Growth prediction remains a central objective in orthodontic planning. AI systems based on cervical vertebral maturation indicators show moderate accuracy, but transitional developmental phases contribute to misclassification.[41–43] Biological variation, environmental influence, and irregular skeletal progression limit the reliability of automated growth forecasting, preserving the necessity of clinical judgment.[44,45] This limitation is particularly consequential in functional appliance therapy and early interceptive treatment, where timing decisions are growth-dependent. A misclassification error at the growth-stage boundary could result in treatment delivered outside the optimal biological window, adversely affecting outcomes. The reviewed studies collectively suggest that AI growth models should be used only as a screening adjunct, with definitive staging confirmed through clinical and radiographic assessment by experienced practitioners.

Automated Cephalometrics and Radiographic Interpretation

AI-driven cephalometric analysis improves efficiency in craniofacial landmarking, but skeletal morphology variations, structural overlap, projection errors, and soft-tissue ambiguity reduce identification accuracy.[27,29,33] Hard-to-localize structures, such as posterior nasal spine or indistinct soft-tissue points, frequently produce inconsistency across platforms, reinforcing that clinician verification remains essential.[31,35] Cephalometric AI is arguably the most mature AI application in orthodontics, yet even here, significant limitations persist. Reviewed studies report that error rates for soft-tissue landmarks consistently exceed those for hard-tissue landmarks, with clinically meaningful deviations (>2 mm) observed in a proportion of automated measurements. The clinical consequence of accumulated landmark errors in angular and linear measurements used for diagnosis and treatment planning has not been adequately quantified in prospective studies, a critical evidence gap that must be addressed before automated cephalometric reports can be used without mandatory clinician review.

Extraction Planning and Decision Support Systems

Extraction planning remains one of the most complex orthodontic decisions. Although some AI models show high concordance with expert recommendations, datasets are often limited to narrow treatment philosophies determined by a restricted pool of clinicians.[10–12] Facial esthetics, skeletal discrepancy, periodontal stability, and patient objectives influence extraction criteria in ways that AI cannot fully interpret.[13,14] Final decisions must be guided by clinical reasoning rather than automated classification. A particularly important critique of current extraction AI models is that they are effectively learning the biases of the clinicians

who labeled the training data. If those clinicians favor or oppose extraction for philosophical rather than purely evidence-based reasons, the model will replicate those biases at scale. This has direct implications for equity in treatment provision and underscores the need for diverse, multi-institutional training datasets with explicit documentation of diagnostic reasoning.

Surgical Case Consideration and Advanced Intervention Forecasting

AI-assisted orthognathic planning demonstrates encouraging predictive performance; however, variation in esthetic standards, facial norms across ethnic groups, and inconsistent clinical benchmarks restrict universal application.[41–43] Complex surgical decision-making requires interdisciplinary evaluation, anatomical appraisal, and esthetic analysis that extends beyond algorithmic capability.[39,40] Orthognathic surgery represents the highest-stakes application of AI in orthodontics, where errors in prediction can translate directly into irreversible surgical outcomes. The reviewed evidence indicates that current AI tools for surgical planning have been evaluated predominantly in East Asian cohorts, limiting their applicability to other ethnic populations. This geographic and demographic sampling bias must be explicitly addressed in future multicentric studies before these tools can be considered for universal clinical deployment.

Ethical, Operational, and Training Barriers

Current challenges extend beyond technical performance. Overreliance on automated results may weaken clinical decision-making skills in younger providers, while nontransparent "black-box" systems complicate accountability during diagnostic conflict.[44,45] Data bias and unequal performance across demographic groups raise concerns regarding fairness, generalizability, and access.[34,35] Until validation standards and legal responsibility frameworks are established, AI must remain a supervised clinical tool, not an autonomous authority. The ethical dimension of AI in orthodontics is not merely theoretical. In jurisdictions where AI-assisted diagnosis or treatment recommendations are used without adequate disclosure to patients, existing informed consent frameworks may be insufficient. Legally, when an AI-generated recommendation contributes to an adverse outcome, the chain of liability between the software developer, the institution, and the treating clinician remains undefined in most regulatory systems. The educational risk is equally significant: residency programs that incorporate AI tools without ensuring that trainees can perform the same tasks independently risk producing clinicians who are dependent on algorithmic support and unable to function competently when systems fail or are unavailable.

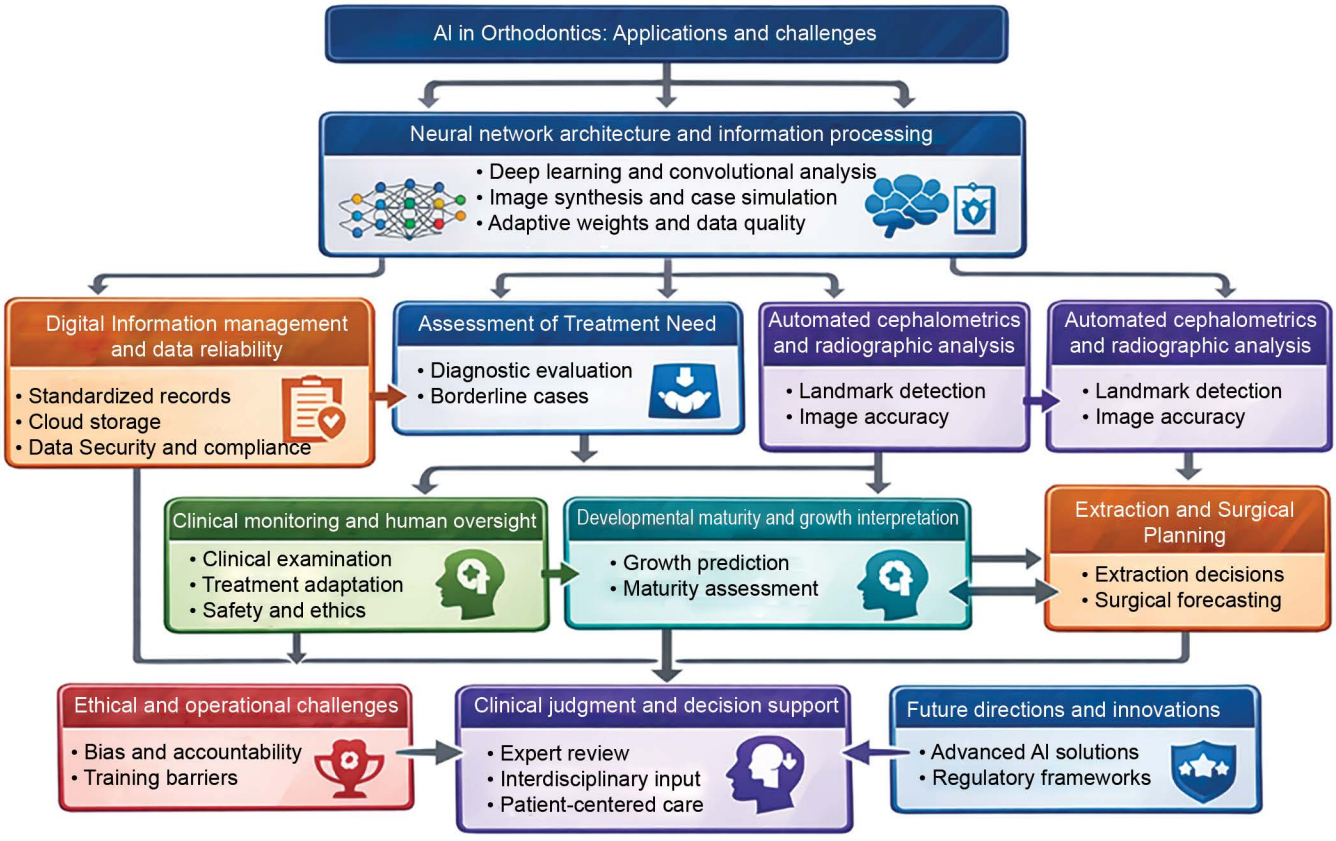

Fig. 1: Schematic overview of the applications and challenges of artificial intelligence in orthodontics, organized across nine functional domains: neural network architecture and information processing, digital information management and data reliability, assessment of treatment need, automated cephalometrics and radiographic analysis, clinical monitoring and human oversight, developmental maturity and growth interpretation, extraction and surgical planning, ethical and operational challenges, and future directions and innovations

Table 1: Key limitations and pitfalls of AI in orthodontics

	Limitations and pitfalls
Data quality and standardization	Inconsistent datasets, missing records, and nonuniform imaging reduce accuracy and limit model reliability
Clinical generalizability	Works well in controlled trials but performs poorly in real-world cases with anatomical, racial, or growth variation
Diagnostic accuracy	Errors in landmark detection, tracing, and cephalometric calculations lead to misinterpretation and treatment risk
Borderline case assessment	AI cannot reliably determine treatment need in borderline cases due to diagnostic disagreement among clinicians
Growth and biological prediction	Skeletal maturity and growth variations cause misclassification; unpredictable biological response reduces trust
Extraction decision planning	Restricted datasets reflect single-clinician philosophy; fails to evaluate esthetics, periodontal state, or patient preference fully
Surgical treatment planning	Lacks universal norms across ethnicities/facial standards; not suitable for final orthognathic decision making
Ethical and legal concerns	Unclear accountability for errors; black-box systems prevent transparency/explanations of decisions
Patient data and confidentiality	Reliance on cloud storage raises privacy, cyber-security, and consent concerns
Human skill dependency	Over-reliance risks reducing critical thinking and diagnostic skills in young practitioners
Algorithm drift and unseen errors	Performance degrades over time if not monitored; small unnoticed errors may escalate in long treatments
Lack of regulatory approval	Few tools are officially validated or licensed; clinical readiness lags behind research progress

Prospective Directions and Evolving Technologies

Future developments may include unsupervised learning methods for phenotype grouping, robotic assistance in precision procedures, and federated learning for secure multicenter data sharing.[14,20] If transparency, regulation, safety monitoring, and benchmarking improve, AI may shift from a supportive adjunct to a central component of orthodontic diagnostics and treatment planning.[35] Federated learning is particularly promising for orthodontics, as it allows multiple institutions to collaboratively train models without transferring sensitive patient data, thereby addressing both privacy concerns and the need for large, diverse datasets simultaneously. Explainable AI (XAI) frameworks represent another critical development priority: tools that provide clinically interpretable justifications for their outputs will be essential for building practitioner trust and regulatory confidence required for broader adoption. Future research should also prioritize prospective clinical trials comparing AI-assisted versus conventional clinical workflows, with patient-centered outcomes such as treatment duration, stability, and satisfaction as primary endpoints. Without this level of evidence, the field risks perpetuating a cycle of incremental technical improvements that never translate into demonstrated clinical benefit (Fig. 1 and Table 1).

Conclusion

Artificial intelligence is steadily reshaping orthodontics by improving diagnostic efficiency, enhancing digital record interpretation, and supporting treatment decision-making. Its strength lies in processing large volumes of information, identifying patterns that may not be immediately visible to the clinician, and providing structured guidance throughout the treatment workflow. However, despite these advancements, AI remains a supplementary resource rather than an independent clinical authority. Limitations in data quality, biological unpredictability, growth variability, and contextual interpretation continue to restrict full automation. In areas such as cephalometric tracing, growth assessment, extraction planning, and orthognathic case evaluation, human expertise is still required to validate digital output, apply clinical reasoning, and ensure patient-centered care.

For AI to progress toward broader acceptance, significant steps are needed, including standardized data collection, consistent validation protocols, ethical safeguards, and transparent model design. Clear regulatory frameworks must be established so that responsibility, accountability, and patient safety are never compromised. Ultimately, the most effective future model is one in which AI and orthodontists work in partnership: the software offering analytical strength and precision, while the clinician provides judgment, experience, adaptability, and empathy. With thoughtful integration and continual refinement, AI has

the potential to complement rather than replace professional practice, leading to safer, more predictable, and more personalized orthodontic outcomes.

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Author Contributions

Vaibhavi Bhimda: Conceptualization, literature search, data collection, data synthesis, manuscript drafting, critical revision, and final approval of the manuscript.
Ajay K Kubavat: Conceptualization, supervision, critical review of content, manuscript revision, and final approval.
Khyati V Patel: Literature review, data interpretation, manuscript revision, and final approval.
Shobhit Saxena: Literature review, manuscript editing, critical appraisal of content, and final approval.
Keyur U Parmar: Supervision, manuscript review, intellectual input, and final approval.

All authors contributed to the study design, reviewed the manuscript, approved the final version.

AI Disclosure

During manuscript preparation, the authors used **Claude AI (Anthropic)** for assistance with language refinement, grammar correction, content organization, and drafting support. All AI-assisted content was critically reviewed, edited, and verified by the authors. No AI tool was involved in data collection, data analysis, interpretation of findings, or clinical decision-making.

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