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Artificial Intelligence In Orthodontics- A Narrative Review

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Abstract
Artificial intelligence (AI) is revolutionising modern orthodontics, enhancing diagnostic precision, treatment planning and clinical efficiency. AI techniques including machine learning (ML) and deep learning (DL) offer automation in cephalometric landmark detection, skeletal maturity assessment, treatment simulation and outcome prediction. Despite these promising applications, concerns remain regarding algorithm accuracy, ethical considerations, data privacy and integration into clinical workflows. This review explores the historical evolution, core applications, advantages and limitations of AI in orthodontics, highlighting the potential challenges of its integration into contemporary orthodontic practice.
Keywords: *Artificial Intelligence; Deep Learning; Machine Learning; Orthodontics.*

INTRODUCTION

Orthodontics is a dynamic dental speciality focused on the diagnosis, prevention and treatment of dental and skeletal malocclusions. Traditional orthodontic diagnosis relies on cephalometric analysis, study models, photographs and clinical assessment. However, these methods are often labour-intensive and susceptible to operator bias and variability. With the rapid advancement of digital technology, a significant transformation is underway through the integration of Artificial Intelligence (AI). AI refers to computer systems capable of performing tasks that traditionally require human intelligence. These tasks include visual perception, speech recognition, decision making and pattern recognition.[1] In the context of orthodontics, AI systems analyse large volumes of patient data including images, records and measurements to assist clinicians in decision making and treatment planning.[2] The underlying technologies include machine learning (ML), deep learning (DL), artificial neural networks (ANNs) and convolutional neural networks (CNNs), each with its unique capabilities and applications in dental imaging and diagnostics.[3] Over the past decade, AI has demonstrated immense promise in transforming orthodontic workflows.[4] Its applications span a wide range of domains including classification of malocclusions, automated cephalometric landmark identification, evaluation of skeletal maturity and airway obstruction and prediction of treatment outcomes, remote monitoring of aligner therapy thereby minimising time and supporting swift treatment decisions.[5] The growing digitization of orthodontic records such as CBCT scans, 3D models and intraoral photographs offers extensive datasets that can be leveraged for training AI systems. This data-driven approach enables personalised, efficient and more predictable care for patients.[6] Although AI offers substantial benefits, incorporating it into orthodontic practice presents certain challenges. Concerns surrounding data privacy, ethical use of AI, clinical validation and regulatory approval remain major barriers to adoption.[7] Moreover, the "black box" nature of many AI models, wherein their internal decision-making processes remains unclear has led many clinicians to be wary of placing full trust in them.[8] As AI continues to evolve, orthodontics stands at the frontier of adopting intelligent technologies to enhance clinical outcomes,reduce inefficiencies and revolutionise patient care. This narrative review aims to explore the historical development, key applications, benefits, limitations and future directions of AI in orthodontics.

HISTORY AND DEVELOPMENT OF AI IN DENTISTRY AND ORTHODONTICS

2.1 Origin of Artificial Intelligence

The theoretical foundation for artificial intelligence was first vocalised by Alan Turing in his 1950 paper “Computing Machinery and Intelligence “and the establishment of artificial intelligence as a discrete field of study occurred at the 1956 Dartmouth Conference, where John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon first formalised the term "Artificial Intelligence".[9,10]

2.2 Evolution of Learning systems: from machine learning to deep learning

The late 20^{th} century marked alternating periods of advancement and stagnation, referred to as the "AI winters," due to computational limits. The subsequent machine learning revolution powered by neural networks and GPU computing, further illustrated that machines could match or surpass human capabilities in specific domains with the emergence of machine learning (ML).[9,11] This advancement was further refined through deep learning (DL), which implemented hierarchical artificial neural networks (ANNs) capable of handling complex pattern recognition tasks such as image analysis,[12] speech recognition[13] and medical diagnosis.[14] These computational breakthroughs established the framework for AI-driven clinical applications, including radiological image interpretation and dental diagnostic automation.

2.3 AI in Dentistry: Initial Applications of Machine Learning for Dental Diagnosis

The pioneering dental AI systems were primarily designed to focus on radiographic diagnostic support, including caries detection and identification of periapical lesions and periodontal diseases.[15,16,17] Subsequent advances in deep learning, particularly convolutional neural networks enabled automated intra-oral image segmentation, prosthodontic design simulation and identification of periapical pathoses and fractures on panoramic radiographs.[18,19,20,21]

2.4 AI in Orthodontics: The New Frontier

The application of AI in orthodontics represents one of the most advanced and rapidly growing segments of dental AI. Unlike other fields of dentistry, orthodontics deals with changes in hard and soft tissues that require monitoring and decision-making based on growth prediction, facial symmetry and tracking tooth movement. The continued digitisation of orthodontic records such as lateral cephalograms, 3D facial scans, intraoral images and digital dental models has provided training AI systems with a large amount of data. Thus, the availability of cloud based storage and high performance computing has made implementation of AI driven platforms in orthodontic clinics and educational settings more feasible. Some landmark studies and tools in orthodontic AI include: WebCeph and CephX: AI powered software for automated cephalometric landmark detection and superimposition [22,23]; Dental Monitoring: A remote monitoring tool using AI to evaluate orthodontic treatment progress from smartphone photos[24]; smart force and smart track (Invisalign): AI-enhanced algorithms for aligner force application and staging. [25]

APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN ORTHODONTICS

3.1 Cephalometric Analysis and Landmark Detection

Orthodontic treatment depends on cephalometric radiographs to evaluate skeletal and dental relationships, ensuring accurate and effective treatment planning. Traditional methods of tracing radiographs proved to be time consuming and error-prone process. These drawbacks were overcome by the launch of AI-powered systems like Convolutional Neural Networks (CNNs) that automated landmark identification and measurement which excelled at image recognition tasks are commonly used to process cephalograms.[26] A pivotal study by Kunz et al. (2020) evaluated an AI system for cephalometric analysis and found no statistically significant difference in landmark identification compared to expert orthodontists.[27] The system demonstrated over 90% accuracy and reduced tracing time by over 75%. In cleft palate patients, who often present complex anatomical variations, Tageldin et al. (2025) showed that AI could still perform robustly, although manual refinement of certain landmarks was necessary for surgical planning.[28] Two cloud-based platforms, namely WebCeph and CephX, offer automated tracing, angular and linear measurements and even superimpositions for treatment progress analysis, making it highly useful in clinical and academic settings. Proving that integration of AI in cephalometric software ensures consistency, reduces diagnosis time and allows large scale orthodontic screenings in epidemiological studies.[29]

3.2 Malocclusion Diagnosis and Classification

The foundation of orthodontic care is accurate diagnosis of malocclusions. AI aids in this process by classifying intraoral photographs and radiographs based on occlusal relationships, arch form, overjet, overbite and spacing. Ryu et al. (2022) developed a CNN model trained on thousands of orthodontic images to classify malocclusion types and image orientation (facial vs. intraoral).[20] Their model achieved over 98% accuracy in categorizing images, which is crucial for AI-driven automated record systems.[20] In addition to that, Tamayo-Quintero et al. (2024) introduced dental arch, an AI tool for identifying arch shape square, ovoid or tapered from dental scans. The model achieved 94.7% accuracy in detecting lower arch forms and 93% in upper arch cases.[21]

3.3 Treatment Planning

Treatment planning in orthodontics is a multidimensional process involving the interpretation of skeletal and dental relationships, facial esthetics and patient specific factors such as age, compliance and growth potential. This process was heavily reliant on clinician's experience and subjective analysis in the past. However, AI now provides data driven assistance to help orthodontists formulate more accurate and individualised treatment plans.

3.3.1 Extraction vs. Non-extraction decision

Determining whether to extract teeth in orthodontic treatment is one of the most debated and consequential decisions. Improper extraction planning may result in compromised esthetics, root resorption or prolonged treatment duration.AI models, particularly deep learning networks like CNNs, have been trained on thousands of patient records to predict extraction needs based on crowding, arch length discrepancies and skeletal relationships. Ryu et al. (2023) used a dataset of over 3,000 occlusal photographs annotated by orthodontists to train four CNN architectures (VGG16, VGG19, ResNet50, ResNet101). The VGG19 model achieved an extraction decision accuracy of 92.2%, with high sensitivity and specificity.[30] Del Real et al. (2022) also developed an AI tool using automated machine learning (AutoML) to predict extraction necessity from digital models and cephalometric data. Their model reached an overall accuracy of 93.9%, showing that AI can outperform less experienced orthodontists in decision making.[31]

3.3.2 Deep Bite and Open Bite Planning

AI has also been applied to guide the correction of vertical discrepancies. El-Dawlatly et al. (2021) designed a decision support system for deep bite correction, which could suggest precise tooth movements (e.g., intrusion of incisors, levelling of curve of spee) based on pre-treatment data. The model achieved a success rate of 94.4%.[32] These AI systems provide detailed biomechanics based protocols, allowing for more predictable correction of complex cases like deep bites and open bites.

3.3.3 Digital Bracket Placement and Virtual Setup

AI is now integrated into software for digital bracket positioning and virtual tooth setups. Tools like Insignia and SureSmile use AI algorithms to determine optimal bracket placement for each tooth, customised to the treatment objectives. This improves treatment efficiency, reduces chairside adjustment time and enhances finish quality.[33]AI-based virtual setups simulate various treatment options (with or without extractions) allowing both clinicians and patients to visualise and compare outcomes.[31,34] These simulations improve treatment acceptance and help in setting realistic expectations.

3.3.4 Appliance Design and Biomechanics

In aligner therapy, AI is essential for staging tooth movements and applying force systems that adhere to biological limits. Align Technology's smartrack and smartforce systems use AI algorithms to predict tissue responses and optimise aligner sequencing for better fit and efficiency.[35]AI-assisted planning software also helps in placing temporary anchorage devices (TADs) by analysing CBCT scans to identify optimal insertion sites based on bone density, root proximity and soft tissue thickness. Tao et al. (2023) used a 3D-Unit AI model to evaluate palatal thickness from CBCT and predict safe zones for mini-implant placement demonstrating AI's role in enhancing both safety and success rates.[36]

3.4 Outcome Prediction and Growth Assessment

Orthodontic treatment extends beyond correcting malocclusions; it also involves anticipating the patient's skeletal, dental, and soft tissue structures changes. By utilising prediction models, the right mode of intervention is chosen, leading to minimised treatment duration and enhanced post-treatment stability. AI systems, trained on large longitudinal datasets are now capable of forecasting these outcomes with increasing accuracy.

3.4.1 Soft Tissue and Facial Morphology Prediction

One of the major concerns in orthodontics is facial aesthetics, especially when planning for orthognathic surgery or extraction based treatment. Traditionally, prediction methods relied on cephalometric overlays and two-dimensional approximations, which had limitations in scope and were often subjective. Tanikawa et al. (2021) developed two AI systems-System S (for surgical cases) and System E (for orthodontic cases) to predict three-dimensional facial soft tissue changes based on pre-treatment lateral cephalograms and facial scans. The models used landmark-based geometric morphometric analysis combined with deep learning algorithms. The results showed a prediction error of less than 1 mm in 98% of non-surgical cases and over 90% of surgical cases, demonstrating clinical reliability.[37] This level of precision enables clinicians to simulate realistic facial outcomes and engage patients in the decision-making process more effectively.

3.4.2 Skeletal Growth Assessment

Treatment planning depends highly on the timing, especially in growing patients. Prediction of mandibular and maxillary growth aids in the determination of the optimal time for interventions like functional appliances, headgear or even orthognathic surgery. Earlier growth assessment relied on methods like hand-wrist radiographs or cervical vertebral maturation (CVM) analysis. However, both are prone to variability and require manual interpretation. Sokic et al. (2012) applied fuzzy C-means clustering and centroid-based analysis on cephalometric radiographs to automate CVM staging.[38] The AI model correctly classified growth stages with >99% accuracy when allowing a ±1 stage error range. This makes growth assessment faster, more consistent and scalable for population-based screening.

3.4.3 Class III Growth Pattern and Relapse Risk Prediction

Class III malocclusion, often associated with mandibular prognathism, carries a high risk of post-treatment relapse due to unpredictable growth. AI is helping to stratify patients based on their relapse risk even before treatment begins. Auconi et al. (2015) applied network analysis and fuzzy clustering on cephalometric datasets of Class III patients. Their model successfully distinguished between phenotypes with good and poor prognosis, based on the interconnectedness of skeletal and dental variables.[39] Such models allow clinicians to: identify high-risk patients early, adjust treatment plans (e.g., delay surgery, opt for camouflage) enhance long-term retention strategies.

3.4.4 Aesthetic evaluation and orthodontic indices

AI systems are also being trained to make aesthetic judgments, mimicking orthodontists' subjective evaluations. Stetzel (2023) developed an AI model using ResNet architecture to assess the aesthetic component (AC) of the Index of Orthodontic Treatment Need (IOTN). The model showed high agreement with expert evaluations, offering a reliable, objective tool for screening and referral.[34] Another study by Ryu J et al. (2023) used AI tools to determine the severity of crowding and determine the need for extraction based on intraoral photographs.[30] This could be especially useful in public health systems to triage cases and optimise specialist referrals based on objective, AI-generated criteria.

3.5 Dental Anomalies Detection

Dental anomalies such as supernumerary teeth, impacted canines, dens evaginatus, hypodontia and other morphological variations pose diagnostic and treatment planning challenges. If not identified early, they can complicate eruption sequences, interfere with alignment and prolong treatment. Traditionally, detecting such anomalies relied on clinician experience and detailed radiographic interpretation. AI is now bridging the diagnostic gap by automating anomaly detection with high precision and speed.

3.5.1 Supernumerary and Impacted Teeth

Impacted canines, particularly maxillary ones, are common in orthodontic cases. Detecting their exact location (palatal or buccal) and spatial relationship to adjacent roots is vital. AI systems trained on panoramic and CBCT datasets can now localise and classify impacted teeth with high diagnostic accuracy. For example, Abdulkreem et al. (2024) trained a deep learning model on panoramic radiographs to detect and classify impacted canines. The model achieved a sensitivity of 92%. It achieved a success rate of 90% for impacted canines and 99% for non-impacted canines.[40] Supernumerary teeth (mesiodens, distomolars, etc.) can disrupt occlusion and delay eruption. A CNN-based model developed by Mine et al. (2023) used 220 radiographs and identified supernumerary teeth with an accuracy of 82.3%, sensitivity of 85.0% and specificity of 79.0 % even in complex mixed dentition stages.[41]

3.5.2 Dens Evaginatus and Morphological Anomalies

Dens evaginatus, an anomalous cusp-like protrusion can complicate occlusion, attract plaque and increase caries risk. Manual detection from occlusal photographs or periapical radiographs is difficult, particularly when the cusp is underdeveloped. Ren et al. (2025) introduced Bi Stage Net, an end-to-end deep learning model designed to detect dens evaginatus on intraoral photographs. The model reached a diagnostic accuracy of 96.5% and offered heatmaps indicating the region of interest. It was particularly effective in young patients where DE is most prevalent.[42,43]

3.5.3 Developmental Abnormalities

AI is being trained to detect anomalies like: hypodontia (congenitally missing teeth) [43], microdontia/macrodontia (size discrepancies) dilaceration (root anomalies), taurodontism (elongated pulp chambers).[44,45,46] Using large CBCT datasets, these features are segmented and classified automatically, aiding early diagnosis and integrated treatment planning.

3.5.4 Pathological Lesions

Although not orthodontic anomalies per se, AI models trained to detect odontogenic cysts, tumours and periapical lesions are proving valuable in orthodontic assessments, especially pre-surgically. A study by Kwon et al. (2020) used deep learning models to identify periapical lesions in the mandible and maxilla from panoramic radiographs with a sensitivity of 88.9% and overall specificity of 97.2%. These tools help to ensure that no pathology is overlooked before initiating movement-based therapies.[47]

3.6 Airway Assessment and Obstructive Sleep Apnea (OSA) Screening

Orthodontists are increasingly involved in identifying and managing airway-related disorders, especially obstructive sleep apnea (OSA) in growing children and adolescents. Malocclusions such as Class II division 1, narrow maxilla and retrognathic mandible have been linked to compromised airway. Traditional airway analysis involves manual measurements on lateral cephalograms or CBCT scans, a time-consuming and subjective process. AI is revolutionising this space by offering fast, objective and repeatable airway evaluations.

3.6.1 Cephalometric-Based Airway Evaluation

Lateral cephalograms provide a two-dimensional approximation of the airway. While limited in volumetric representation, they are useful for preliminary screening. Jeong et al. (2023) trained a UNet with an Efficient NetB0 model through the region of interest-centered circular segmentation labelling process for detecting upper airway (UA) soft tissue landmarks in comparison with the skeletal landmarks on the lateral cephalometric images.[48] This model helped clinicians flag high-risk cases for further CBCT or polysomnographic evaluation. Another study by Zhao et al. (2021) generated and evaluated an automatic detection algorithm for adenoid hypertrophy in lateral cephalometric images using a convolutional neural network intelligence system.[49] The system was able to detect AH with an accuracy, sensitivity and specificity of 95%, offering faster diagnosis than manual tracing.

3.6.2 CBCT-Based Volumetric Airway Analysis

Cone-beam computed tomography (CBCT) allows three-dimensional airway evaluation, providing data on volume, cross-sectional area and constriction points. However, interpreting CBCT slices requires extensive manual segmentation. To address this, Dong et al. (2023) developed HMSAU-Net (a hybrid U-Net architecture) and 3D-ResNet to segment and classify adenoid hypertrophy, a common cause of airway narrowing. These models achieved a Dice similarity coefficient of 0.96 and a classification accuracy of 91.2%. [50] Such models can segment nasopharyngeal and oropharyngeal airways, detect anatomical deviations and even grade airway obstruction severity. This is particularly useful in planning interventions like Rapid Maxillary Expansion (RME), mandibular advancement devices or referring for ENT evaluations.

3.6.3 Integrating Airway AI in Clinical Workflow

Modern platforms like Airway Metrics Pro, Romexis AI and On Demand 3D now integrate AI-powered airway analysis into CBCT reading tools.[51] They offer automatic segmentation of nasopharyngeal, oropharyngeal and hypopharyngeal regions, volume and constriction calculations before and after the treatment. This empowers clinicians to demonstrate to patients how their airway dimensions change over time, especially after interventions like RME, mandibular advancement or bimaxillary surgery.

3.7 Remote Monitoring and Clear Aligner Therapy

The emergence of teledentistry and the popularity of clear aligner therapy (CAT) have accelerated the demand for remote orthodontic monitoring systems. AI now plays a critical role in tracking tooth movement, aligner fit, oral hygiene and treatment progress without requiring in-person visits. This is especially valuable in enhancing patient compliance thereby reducing chair time.

3.7.1 AI-Enabled Remote Monitoring Platforms

Dental Monitoring (DM) is the leading AI-powered tele dentistry platform in orthodontics.[52] It uses deep learning algorithms trained on millions of intraoral images to track aligner fit and seating, monitor tooth movement stage-by-stage, detect broken attachments or oral hygiene issues, send automated alerts to both patient and clinician when intervention is needed.The AI system compares images to the expected tooth positions and flags discrepancies in real time. A systematic review by Sangalli et al. (2023) showed that DM reduced in-office visits by 30–40%, without compromising treatment quality. Moreover, AI-identified issues (e.g. poor aligner fit) correlated strongly with manual evaluations by orthodontists.[52]

3.7.2 AI in Aligner Staging and Force Application

Planning the sequence of tooth movements is one of the most challenging parts in the treatment planning of clear aligners. Align Technology, the parent company of Invisalign, uses AI in two key systems: smart track, a proprietary aligner material optimised via AI simulations for flexibility, precision and smart force, AI-generated force application features (attachments, pressure points) that deliver more efficient movements.[35]AI determines not only the optimal path for each tooth but also designs customised force elements to achieve it with fewer refinements.

3.7.3 Virtual Consultations and Screening

Instant assessments of orthodontic status can be received from certain AI-based apps that allow patients to take selfies or intraoral photos. These platforms offer: malocclusion type predictions (e.g., Class II, crowding), smile score aesthetic evaluations (smile view), recommendations to consult a specialist thereby offering tools valuable for initial screenings.[53]

3.7.4 Compliance Monitoring

Orthodontic treatment using aligners requires patient compliance for achieving results. AI systems track: aligner wear time (via sensors or image tracking) missed aligner days, progress stagnation (movement plateau alerts).[54] Some systems integrate gamification, providing points, reminders or rewards for consistent scanning and proper wear. This increases engagement and improves outcomes.

ADVANTAGES OF AI IN ORTHODONTICS

AI, along with a sound orthodontic practice, offers a wide array of benefits, spanning clinical precision, operational efficiency, patient experience and research advancement. Some of the key advantages that AI brings to orthodontics are:

4.1 Improved Diagnostic Accuracy

AI algorithms particularly convolutional neural networks (CNNs) have demonstrated diagnostic precision equal to experienced clinicians in various orthodontic tasks such as cephalometric landmark identification, malocclusion classification and airway assessment. For example, Kunz et al. (2020) reported >90% accuracy in automatic cephalometric tracing and Ryu et al. (2023) achieved over 98% accuracy in diagnosing crowding and identifying extraction needs.[27,30] This level of accuracy ensures early and correct diagnosis which is fundamental to treatment success.

4.2 Enhanced Clinical Efficiency

Manual tasks such as landmark identification, treatment simulation, and progress monitoring can consume hours of clinician time. AI dramatically reduces this workload: Cephalometric tracing time is cut from 30–45 minutes to less than 30 seconds. Remote monitoring reduces the number of in-person appointments by 30–50%.[52] Automated growth assessment tools eliminate the need for auxiliary radiographs.[38] This efficiency not only optimises clinic operations but also enhances patient satisfaction.

4.3 Standardisation and Reduced Operator Bias

Traditional treatment planning and diagnosis are subjected to inter and intra-operator variability, especially in subjective assessments like smile esthetics, soft tissue profiles and treatment need scoring.

On the contrary, trained AI models can overcome these limitations. For example, AI evaluations of IOTN-aesthetic component show high reproducibility.[34] Cephalometric software ensures uniformity in landmark placement and measurement.[27,28] Standardisation is especially useful in multi-clinician practices, teaching institutions and research trials where consistency is critical.

4.4 Personalised and Predictive Treatment

Customised treatment plans created based on patient-specific data are an added advantage for using AI models. Unlike conventional treatment templates, AI considers: facial symmetry,[37] growth patterns,[38] behavioural compliance (e.g., aligner wear)[52] airway dimensions,[48-51] soft tissue adaptation.[37] Predictive models simulate facial changes, skeletal growth and relapse risks. This empowers orthodontists to proactively plan interventions and set realistic expectations with patients.

4.5 Improved Patient Engagement and Satisfaction

AI-powered visual tools are equipped to run smile transformation simulations or facial profile predictions, aiding patients to visualise and understand potential outcomes. Thus, boosting confidence and acceptance. Remote monitoring apps with real-time feedback: enhanced communication, reduced unnecessary travel and promotes treatment ownership. Gamified platforms for compliance tracking further improve aligner wear and oral hygiene.

4.6 Data-Driven Research and Continuous Learning

AI's ability to analyse vast datasets enables large-scale orthodontic research. AI uncovers hidden patterns and correlates patient data better than traditional statistical analysis, such as: factors influencing class III relapse,[39] ideal biomechanics for molar intrusion, correlations between airway volume and craniofacial form.[48] Additionally, AI models improve with ongoing data exposure, offering a self-enhancing mechanism rarely seen in traditional tools.

CHALLENGES AND LIMITATIONS OF AI IN ORTHODONTICS

Artificial intelligence in orthodontics comes with its own set of challenges despite its growing adoption and potential. Several ethical, technical and regulatory barriers must be addressed before its integration into our day-to-day life.

Data Dependency and Quality

These AI systems rely on huge datasets for training and validation. These datasets must be large enough to capture clinical diversity, accurate, annotated, de-duplicated and most importantly, should represent diverse populations and malocclusion types.[55] But unfortunately, most of the current datasets are restricted toward certain ethnicities, age groups, or appliance types, derived from a single region or interpreted inconsistently by different clinicians.[55,56] This compromises generalizability. For example, a CNN trained to detect Class II cases using data from adults may underperform when applied to growing children or mixed dentitions.

Algorithmic Bias

AI models can sometimes amplify or inherit biases present in training data. For example, it could under represent certain craniofacial phenotypes leading to misclassification and if most training records came from private practices, the model may be less applicable to underserved populations with different disease patterns.[57] This may result in healthcare disparities when used in a public setting.

Lack of Transparency (Black Box Problem)

Most of the AI models are non-explainable systems, which means that most of their internal decision-making processes are opaque to users. This is called a "black box" problem.[58] It makes it difficult for users to verify how or why a particular diagnosis/prediction was made, correct errors or biases within the model and to gain trust from clinicians and patients. Addressing this challenge is critical in healthcare, where accountability and understanding are crucial.

Clinical Validation and Integration

Many AI tools are confined to the laboratory and lack real-world clinical validation. These systems must undergo rigorous clinical trials (randomised, multi-centre, prospective) comparative studies against human experts and validation across different software, hardware and imaging formats to be integrated into daily life.[55] Furthermore, integrating AI tools into daily workflow needs software compatibility with existing systems, clinician training and acceptance along with infrastructure investment (e.g., high-speed internet, cloud storage).

5.5 Legal and Ethical Concerns

Key ethical and legal challenges include,[59]

Data Privacy: Patient records used in AI training must comply with privacy regulations (HIPAA, GDPR) and cloud-based tools must be secure.

Informed Consent: Patients may not fully understand how their data will be used or how AI influences their treatment.

Liability: If a treatment error occurs based on an AI recommendation, it's unclear whether responsibility lies with the developer, clinician or institution.

Regulation: Most countries lack specific guidelines for dental AI devices. The FDA, CE and other regulatory bodies are still developing frameworks.

Resistance from Clinicians

Like all health care fields, orthodontics has a strong human-centred tradition. Many clinicians may distrust AI tools due to a lack of explainability, fear of replacement or loss of autonomy or simply prefer traditional experience-based approaches. To overcome this resistance, clear demonstration of AI's reliability and emphasis on AI as a supportive tool can be done.

FUTURE DIRECTIONS AND INNOVATIONS

With the recent increase in computational power, greater access to data and growing clinician interest, AI is set to become an integral part of the field of orthodontics. Several trends and innovations are expected to shape the next decade of AI-driven orthodontics.

Development of explainable AI (XAI)

Every decision made needs a justification and that is the reason researchers are now working on explainable AI (XAI) to overcome the "black box" dilemma. These systems, apart from making predictions, also provide visualisations or narratives to justify their decisions. For instance, XAI could highlight specific regions of a radiograph responsible for identifying a decayed tooth.[60] This explainability will improve a clinician's trust, ease regulatory approval and facilitate patient communication.

6.2 Federated Learning for Privacy-Safe AI

The orthodontic community is exploring federated learning, a framework where AI models are trained on decentralised data sources without transferring patient data to a central server to help battle the issue of data privacy. Each orthodontic clinic can train the AI locally; only the learned model weights (not patient records) are shared.[61] This can preserve data security, promote multi-institutional collaboration and increase dataset diversity.

AI-Integrated 3D Printing and CAD/CAM Systems

Cutting-edge technology can be incorporated into the manufacturing of orthodontic appliances including aligners, retainers and customised brackets with the help of AI and its integration with 3D printing and CAD/CAM, thus allowing faster appliance turn around, more precise force application, improved patient comfort and efficiency.AI-driven bracket placement guides are being developed to factor in crown/root angulation, bone thickness and aesthetic goals.[62,63,64,65]

Real-Time Chairside AI Assistants

Latest developments like AI-powered chairside assistants have proved to help clinicians and consultants.[66] These systems can pull up similar cases with documented outcomes and suggest possible interventions or biomechanics along with the generation of on-the-spot simulations for patient education thereby enhancing patient engagement and accelerating decision-making.

Multimodal AI Systems

Presently, most AI models are trained on a single data type (e.g., images or measurements) but the upcoming multimodal AI can combine CBCT imaging, facial scans, cephalometric data, electronic health records (EHRs) and genetic profiles.[67] A combination of these systems can provide deeper, personalised insights into treatment outcomes, relapse risks and long-term prognosis.

CONCLUSION

The recent digitisation of orthodontic records brings us to a point where artificial intelligence is not just a futuristic concept, it is already transforming orthodontic practice today, from diagnostic accuracy to predictive modelling, remote monitoring and patient-specific treatment planning. Federated learning, explainable AI and multimodal systems will make AI safer, more ethical and more insightful. In conclusion, it can be regarded as a time-saving tool to supplement the traditional orthodontic management strategies.

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