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Artificial intelligence in bone age assessment for orthodontic treatment planning: a review of current evidence

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ABSTRACT

Background: The accurate timing of orthodontic intervention depends primarily on assessment of a patient's residual growth potential. Conventional diagnostic approaches, such as cervical vertebral maturation (CVM) analysis and hand-wrist maturation (HWM) assessment, are subjective methods that rely solely on the clinician's visual interpretation. This study aimed to determine the extent to which artificial intelligence (AI), including deep learning (DL) algorithms, can be used to automate and standardise bone age assessment in orthodontic treatment planning. *Methods*: A structured narrative review was conducted. PubMed, Web of Science, Scopus, and Google Scholar databases were searched for articles published from January 2021 to March 2026. For the final analysis, 40 articles were selected. *Results*: Research shows that neural networks, such as convolutional neural networks (CNNs), can very well recognize the maturation stages of the cervical vertebrae and the bones of the hand and wrist. In selected studies, their accuracy exceeded 90%. Explainable AI, 3D CBCT analysis, and systems that combine multiple data types can improve the clarity, reproducibility, and clinical utility of such tools. *Conclusions*: Artificial intelligence may be helpful in decision-making and thus reducing diagnostic time and supporting the standardization of orthodontic treatment planning. Future research on multimodal systems, data protection, and transparent decision-making is needed.

Keywords: artificial intelligence; orthodontics; cervical vertebral maturation; bone age assessment; skeletal maturity

1. INTRODUCTION

The Importance of Treatment Timing in Orthodontics

Accurate determination of treatment timing remains a fundament of success in orthodontic and dentofacial orthopaedic therapy. Recent investigations indicated that craniofacial development and skeletal maturation were governed by multifactorial biological variables (Liu et al., 2023; Oliveira et al., 2025). Current research emphasises that therapeutic interventions aimed at modifying growth need to be initiated either directly during the pubertal growth spurt or shortly prior to its onset (Sadeghi et al., 2025; Mohammad-Rahimi et al., 2022). The patient's remaining growth potential can be effectively utilised, depending on the timing, particularly in cases requiring orthopaedic correction of sagittal or transverse skeletal discrepancies.

Conventional Methods of Skeletal Maturity Assessment

Orthodontists rely on several somatic indicators of skeletal development to determine biological age. For many years, the hand-wrist maturation (HWM) method has been regarded as the reference for evaluating skeletal maturity. It is based on the appearance, enlargement, ossification of the phalanges, metacarpals, and carpal bones in RTG. The most common staging systems are Fishman Skeletal Maturity Index (SMI) and Björk's method (Farzanegan et al., 2025; Kazimierczak et al., 2024). HWM has a long history, but possible benefits from additional exposure to radiation have to be weighed against the ALARA principle, which emphasises minimising radiation exposure whenever possible (Kim et al., 2023; Tentaş and Özden, 2025). Therefore, cervical vertebral maturation (CVM) assessment has gained popularity. Its primary advantage is that it uses standard lateral cephalometric radiographs, which are already obtained as part of routine orthodontic diagnosis, and eliminates the need for additional RTG (Ghergie et al., 2025; Li et al., 2022; Li et al., 2023). The CVM method categorizes skeletal maturation into six stages (CS1-CS6). Staging is based on morphology of the second, third, and fourth cervical vertebrae (C2-C4). In early developmental stages, the vertebral bodies are flat and trapezoidal. In later stages they become concave and rectangular, which is typical of the final stages of maturation (Kavousinejad et al., 2024).

Limitations of Conventional Visual Assessment and Rationale for AI Integration

The assessment of CVM depends on the clinician's experience. Moving from one stage of maturation to the next is gradual. There isn't a clear-cut boundary – in borderline cases, different doctors might give a different result.

According to research, the agreement between doctors' assessments is often only moderate. The kappa agreement coefficient usually ranges around 0.5-0.7 (Sadeghi et al., 2025; Kavousinejad et al., 2024; Kanchanapiboon et al., 2024). Mistakes between adjacent stages can matter—for example, CS3 and CS4. A doctor might start treatment with a functional appliance either too early or too late. As a result, the effect of utilizing the patient's growth will be weaker. Artificial intelligence can help reduce such differences. Convolutional neural networks - CNNs, are especially useful. The program analyses an image (pixel by pixel) and automatically finds important features. For example, the shape of a circle or a dip in its bottom edge. You don't have to manually mark all the points.

The biggest benefit of AI isn't just speeding up work, but the ability to apply the same criteria to every image. This makes the results more consistent. AI is meant to support the doctor, not replace them. The goal of this review was to see what's currently known about using AI to assess skeletal maturity in orthodontics.

2. REVIEW METHODS

This research was carried out using a narrative review of the current literature. The literature search was conducted in April 2026 according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for study selection. The online databases used included PubMed, Web of Science, Scopus, and Google Scholar. The search was focused on peer-reviewed articles written between January 2021 to March 2026, and the keywords used included: (artificial intelligence OR deep learning OR machine learning OR neural networks) AND (cervical vertebral maturation OR bone age OR skeletal maturity OR midpalatal suture) AND (orthodontics OR cephalometry OR CBCT).

The database search initially identified 400 records (PubMed: n = 220; Google Scholar: n = 180). After removing 110 duplicates, 290 titles and abstracts were screened, resulting in the exclusion of 215 non-relevant studies. The remaining 75 full-text articles were evaluated for eligibility, from which 35 were excluded due to inappropriate study designs or non-relevant outcome measures. Ultimately, 40 publications met all eligibility criteria and were included in the review. The systematic identification, screening, and selection process is illustrated in the PRISMA flow chart (Figure 1).

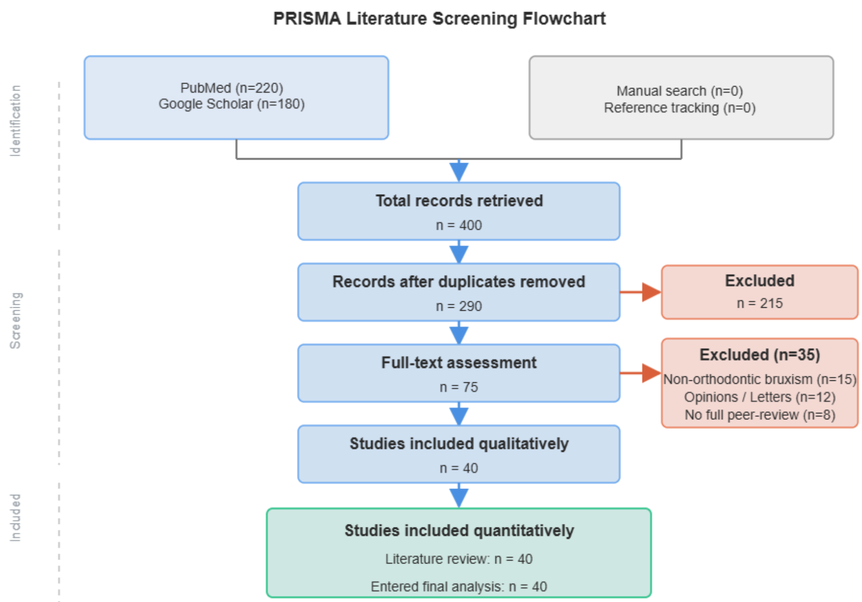

Figure 1. PRISMA flow diagram outlining the database search, screening, eligibility assessment, and final study selection process.

3. RESULTS AND DISCUSSION

Deep Learning in the Analysis of Cervical Vertebral Maturation (CVM)

Recently, deep learning methods have become more popular for the automated analysis of lateral cephalometric radiographs (Liu et al., 2023). Previously, the classification of skeletal maturity has been performed using systems like ResNet, Inception, and VGG. The programs assessed the shape of the C2–C4 vertebrae, the depression of the inferior border, and the ratio of vertebral height to width (Agarwal and Agarwal, 2022; Seo et al., 2021; Zhou et al., 2021).

In some studies, CNNs achieved accuracy of over 90% in recognising CVM stages. In one study, a ResNet-50-based model achieved approximately 94% correct classifications. The results were similar to those of experienced physicians. Sometimes even better than the average agreement between them (Agarwal and Agarwal, 2022). Crucially, the program applies the same principles to a large number of images. The advantage of these systems is not only the automation of the processes but also the ability to use uniform analytical criteria for large data sets. Deep learning models can contribute to improved reproducibility of skeletal maturity assessment in routine orthodontic practice by reducing inter-clinician variability associated with visual assessment of disease severity. The main applications of artificial intelligence in orthodontic skeletal maturity are shown in Table 1.

Table 1. Main applications of artificial intelligence in orthodontic skeletal maturity assessment

Area of application	Imaging or data source	AI approach	Clinical purpose	Potential benefit
Cervical vertebral maturation classification	Lateral cephalometric radiographs	Convolutional neural networks, including architectures such as ResNet, VGG, and Inception	Automated classification of cervical vertebral maturation stages	May reduce observer variability and support standardized skeletal maturity assessment
Multistage CVM analysis	Lateral cephalometric radiographs	Sequential models combining localization, segmentation, and classification	Automated identification of the cervical vertebral region and stage classification	Improves anatomical focus and may reduce the influence of irrelevant image structures
Quantitative vertebral analysis	Lateral cephalometric	Deep learning combined with landmark- or	Assessment of vertebral shape, inferior border	May improve differentiation between

	radiographs	contour-based measurements	concavity, and height-to-width ratios	transitional maturation stages
Hand-wrist skeletal maturity assessment	Hand-wrist radiographs	Object detection and deep learning models, including YOLO-based approaches	Identification of ossification centers and skeletal maturity indicators	Enables faster image analysis and may improve workflow efficiency
CBCT-based skeletal maturity assessment	Cone-beam computed tomography	Three-dimensional deep learning and quantitative volumetric models	Evaluation of cervical vertebral or sutural maturation in three dimensions	Reduces anatomical superimposition and may improve segmentation precision
Explainable AI in orthodontic imaging	Radiographs or CBCT images	Grad-CAM and other visualization methods	Identification of image regions influencing model decisions	Improves interpretability and may increase clinician confidence
Multimodal maturity assessment	Imaging data combined with age, sex, dental development, and skeletal markers	Multimodal deep learning and attention-based fusion models	Integration of multiple growth-related indicators	May provide a more comprehensive assessment of individual growth status

Multistage Models and the Role of Quantitative Analysis

Soft tissue, the hyoid bone, teeth, or other structures may obstruct the vertebrae. That is why single-step analysis is not always optimal (Rana et al., 2023). Systems have been developed that analyse images in stages. For example, psc-CVM, which was trained on 10,200 cephalometric images (Li et al., 2023), first identifies the C2–C4 vertebral area, separates their contours from the surrounding area, and finally determines the maturation stage based on the vertebral shape. A similar approach has been described in the CVnet model. It was evaluated using more than 2,000 cephalograms (Jiang et al., 2025). In addition to the global shape recognition, this system recognises several mathematical reference points along the vertebral borders. The model combines qualitative pattern recognition and quantitative measures, such as vertebral height to width ratios, or depth of inferior border concavity. Simultaneous image recognition with measurements helps distinguish between transitional stages of analysis and reduces final errors (Kavousinejad et al., 2024; Abdulqader et al., 2025; Motie et al., 2025). Newer models attempt to both predict the CVM stage and predict the direction and strength of subsequent mandibular growth. Although still in the research phase, this is a promising direction for future AI development (Mohammad-Rahimi et al., 2022; Shoari et al., 2024; Mohammed et al., 2024).

Expanded Field of View and Three-Dimensional (CBCT) Approaches

By limiting the analysis to a specific region of interest (ROI), we can simplify model training. It may also reduce the amount of contextual information available for interpretation. Scientists have indicated that models that assess the entire lateral cephalometric radiograph may provide higher overall accuracy than models that only analyse the cervical vertebral segment (Kim et al., 2024). Including larger craniofacial structures could lead to discovering other patterns related to tissue growth. This concept has been used to design large-scale architectures, e.g. ARNet-v2, to analyse full cephalometric images in relation to the timing of pubertal growth. Such models have demonstrated significantly less classification errors in validation studies compared to conventional visual staging methods (Kim et al., 2025). This broader analytical approach may provide an integrated view of skeletal maturation from a clinical perspective. Another improvement has been the shift from two-dimensional (2D) radiographic assessment to three-dimensional (3D) volumetric assessment by cone beam computed tomography (CBCT). With the advances in CBCT imaging, volumetric data with high resolution and isotropic voxels can be obtained. It improves the visualisation of vertebral anatomy. Intelligent assessment of skeletal maturation using three-dimensional volumetric data has been developed using quantitative models based on CBCT-derived cervical vertebral parameters (Xie et al., 2022).

Conventional lateral cephalograms produce 2D views with overlapping of bilateral anatomical structures. Three-dimensional analysis solves this problem. It eliminates superimposition. On 2D radiographs, dental shadows, mandibular outlines, as well as soft tissues interfere with the view of vertebrae. Because volumetric scans do not have this interference, they yield much more accurate segmentations. Not enough data from certain growth phases is another issue. The CS3 stage represents the peak of pubertal growth, but samples are rare in current databases because its features are morphologically subtle. Generative methods can create additional training data to balance group sizes. However, this data should be carefully checked (Qu et al., 2022).

The "Black Box" Concern: The Role of Explainable AI

"Black box" is an AI phenomenon in which a clinician is unaware of the precise decision-making process behind a given interpretation. It reduces trust in the AI analysis. Explainable AI, or XAI, offers a solution. Tools such as Grad-CAM create a colour map on the image, which shows areas the program paid the most attention to. In the case of CVM, this could include, for example, the lower edges of the vertebrae, their depressions, or the height-to-width ratio. This allows the doctor to verify whether the program analysed the correct structures (Nordblom et al., 2024). XAI does not replace the doctor's judgment. It facilitates the assessment of whether the program's output makes sense. Such transparency will also be important from an ethical and legal perspective.

Skeletal Age Assessment Based on Hand-Wrist Radiographs (HWM)

Although cervical vertebral maturation has become increasingly favoured because of the absence of additional radiation exposure, hand-wrist radiography remains an established component of skeletal growth assessment. For many clinicians, hand-wrist analysis continues to provide valuable complementary information, particularly in complex or borderline cases such as skeletal dysplasia. Systems have been developed that automatically locate ossification sites in an image and assess the degree of bone fusion in the fingers, metacarpals, and wrists. These models include YOLO. Studies have shown that AI can learn the Fishman, Björk, Hägg, and Taranger methods and perform similarly or better than physicians (Kim et al., 2023; Tentaş and Özden, 2025). Deep learning algorithms are being continuously more advanced. They now enable automated bone age assessment from hand-wrist radiographs (Lee et al., 2017). It can decrease the time of image interpretation in clinical setting. In one study, the average image reading time decreased from 22.3 to 17.2 seconds after using AI (Jeong et al., 2025).

Large-scale models combining language and image, similar to ChatGPT can analyse a wide range of image types, but currently, specialised convolutional neural networks trained on specific medical images are more accurate at precisely estimating bone age. Generic models can sometimes produce false explanations and therefore require separate medical validation (Yıldırım et al., 2025).

Multimodal Approaches and Emerging Perspectives

Newer models assess multiple anatomical structures rather than focusing on one. As an example, DeepMSM assesses palatal suture maturity using CBCT, taking into account appearance of the suture, patient's age, biological sex, CVM stage, and, in selected cases, the development of the roots of the third molars (Cai et al., 2025; Biskupovic et al., 2026). The system predicts the degree of maturity by combining the data. In selected studies, accuracy exceeded 90%. This can be helpful in distinguishing different stages of suture fusion, which is important when choosing a maxillary expansion method. In younger patients, simple rapid maxillary expansion is possible, but in older adolescents and young adults, in whom the suture is more fused, surgically assisted rapid maxillary expansion (SARPE), may be necessary. Systems combining bone age and dental age to improve the accuracy of child development assessment have also been studied (Pinchi et al., 2026).

Other studies have assessed the spheno-occipital synchondrosis and the size of the frontal sinus as an additional indicator of maturity when the cervical vertebrae are poorly visible (Milani et al., 2025; Alfawzan, 2023). New concepts also include circum-maxillary suture maturation assessment to improve the timing of orthopaedic interventions in patients with Class III malocclusion (Dong et al., 2026). Researchers are also exploring the integration of AI into the Metaverse to create patient "Digital Twins". It could support the development of virtual patient-specific diagnostic environments. Such solutions, when fully developed, could help with more personalised treatment planning (Moztarzadeh et al., 2023).

Challenges, limitations and future perspectives

AI in orthodontics has promising capabilities. On the other hand, it is not used in day-to-day practice. The main challenges restricting the broad implementation are related to ethics, methodology, and technical difficulties (Oliveira et al., 2025; Farzanegan et al., 2025). The first problem is the data quality because AI model learns from examples labelled by experts, who make mistakes. This leads to the model learning incorrect interpretations based on those errors. Thus, training images must be carefully selected and evaluated by experienced specialists (Kanchanapiboon et al., 2024). This alone diminishes AI's position in medicine. The second problem is data diversity. One model cannot be used for image interpretation in patients whose data were not included in the training process. Otherwise, it could lead to malpractice. There is a need to use demographically diverse cohorts, reduce bias, and validate models on a broad population before implementation (Martín Pérez et al., 2025).

Data privacy can be an issue. Large-scale AI training typically requires the aggregation of radiographic datasets from multiple institutions. Regulatory frameworks, such as the European General Data Protection Regulation (GDPR) and the U.S. Health Insurance Portability and Accountability Act (HIPAA) impose strict limitations on sharing identifiable medical data. Concerns regarding cybersecurity and unauthorised access further complicate the use of centralised data storage systems. A solution to this could be federated learning. It requires the algorithm to be distributed to participating institutions. It is then trained on local datasets, and in the end, only the updated model parameters are sent back to the central server. Patients' data is therefore kept in the internal system, reducing privacy risks while enabling collaborative model refinement (Zhang et al., 2022). This method, however, is not easy to implement, because federated systems require robust infrastructure and standardised implementation protocols. Another issue is medical responsibility.

Currently, AI is intended to be a supportive tool, not an independent diagnostician. Each diagnosis, treatment plan, and therapeutic decision based on AI should be treated as a suggestion and needs to be analysed by an orthodontist. Failure to meet this obligation can lead to inappropriate timing of growth modification or unnecessary extraction (Duggal and Tripathi, 2024). The principal challenges and future directions for clinical implementation of AI-based skeletal maturity assessment are summarised in Table 2.

Table 2. Challenges and future directions in AI-based skeletal maturity assessment

Challenge or future direction	Current issue	Clinical relevance	Suggested direction
Dataset quality	AI models depend on the quality and consistency of training labels	Inaccurate or inconsistent labels may lead to unreliable predictions	Use carefully curated datasets with expert consensus labeling
Inter-observer variability	Conventional skeletal maturity staging is partly subjective	Differences between clinicians may affect treatment timing	Use AI as a decision-support tool to improve reproducibility
External validation	Many models are trained and tested on limited or single-center datasets	Performance may decrease in different populations or clinical settings	Perform multicenter and cross-population validation studies
Class imbalance	Transitional stages, especially clinically important growth peak stages, may be underrepresented	Misclassification may affect the timing of orthopedic treatment	Apply balanced datasets, augmentation methods, and stage-specific validation
Explainability	Deep learning systems may function as "black box" models	Lack of transparency may reduce clinician trust	Incorporate explainable AI tools such as activation maps
Radiation protection	CBCT-based approaches provide detailed three-dimensional data but involve higher radiation exposure than two-dimensional imaging	Pediatric orthodontic patients require careful justification of imaging	Avoid CBCT solely for skeletal maturity assessment when two-dimensional imaging is sufficient
Data privacy	AI development often requires large multicenter datasets	Patient radiographic data are sensitive medical information	Consider privacy-preserving approaches such as federated learning
Clinical responsibility	AI systems may support diagnosis but should not make autonomous treatment decisions	Incorrect reliance on AI may affect treatment planning	Maintain clinician oversight and use AI as an adjunctive tool
Future multimodal systems	Single-anatomy assessments may not fully capture biological maturity	Growth evaluation is multifactorial	Integrate CVM, dental development, sutural maturation, and patient-related variables

4. CONCLUSION

Machine learning and deep learning techniques, mainly convolutional neural networks, can be considered reliable for automated bone age evaluation. The current study results have proven that such methods, if applied correctly, can produce results comparable to those obtained by clinical professionals for classification of CVM and hand/wrist morphology analysis. To address the so-called "black box" problem, one may use explainable AI methods, for example, Grad-CAM maps that can demonstrate how particular regions in an image affect the result. A federated learning approach may also be used since, in it, patient data stay at the source facility, thus providing better data protection. Creating neural network-based workflows will allow AI-supported bone age assessment to be incorporated into clinical processes, making the process faster and more reproducible. Still, one should keep in mind the important role that the doctor plays in the process; such solutions are meant to support analysis, but not to replace the physician's judgment. Prospective progress in digital orthodontics will probably go in the direction of creating multi-modal solutions where several types of data are analyzed. AI is still an auxiliary technology, and the responsibility for diagnosis and treatment decision-making belongs to the clinician.

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Authors' Contributions

Erwin Górski: conceptualization, writing – review and editing. Amelia Sobanek: conceptualization. Filip Szewczyk: methodology. Jakub Deptuch: formal analysis. Zuzanna Szczerba: investigation, writing – review and editing. Weronika Kubiak: writing – original draft preparation. Aleksandra Wyciślok: data curation. Justyna Koziarska: supervision. Aleksan-dra Pietrzyk: writing – review and editing. All authors have read and approved the final ver-sion of the manuscript.

Informed consent

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Ethical approval

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Conflict of interest

The authors declare that they have no conflicts of interest, competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data and materials availability

All data associated with this study will be available based on the reasonable request to corresponding author.

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