Development of an AI Model for Predicting Skeletal and Soft Tissue Changes After Orthognathic Surgery: A Systematic Review

Alhaitham W. Almohawis[1], Abdulfattah Mohammed Al-Awadhi[2], Eslam Hassan Attieh[3], Osama Abdullah Al Zahrani[4], Ali Fahad Alshammari[5], Ahmed Moustafa Abdelnaby Mansour[6], Mothana Saleh Alghamdi[7], Ekram Alsadig Malik Ateeg[8], Muath Mansour Alwehaibi[9], Mashael Muteb Alharthi[10], Azza Ahmed Khalid Mohammed[11], Mohammed Adeeb Bin Talib[12]

[1]Oral and Maxillofacial Surgery, Awalmohawis@imamu.edu.sa
[2]Senior Specialist in Oral and Maxillofacial Surgery, ab.fattah95@gmail.com
[3]General Dentist, Mreack@gmail.com
[4]General Dentist, osamalbashiri@outlook.com
[5]General Dentist, Mthor875@gmail.com
[6]Advanced General Dentist, birdflu100@gmail.com
[7]General Dentist, Dr.alghamdims@outlook.sa
[8]General Dentist, ikramelsadig@gmail.com
[9]General Dentist, Muath.m.10@gmail.com
[10]Dentistry, Mashaelaharthi@gmail.com
[11]GP Dentist, azza.a.khalid@gmail.com

[12]Dentistry, Oral and Maxillofacial Mo0ody2001@Outlook.Sa

HOW TO CITE:
Alhaitham W. Almohawis, Abdulfattah Mohammed Al-Awadhi, Eslam Hassan Attieh, Osama Abdullah Al Zahrani, Ali Fahad Alshammari, Ahmed Moustafa Abdelnaby Mansour, Mothana Saleh Alghamdi, Ekram Alsadig Malik Ateeg, Muath Mansour Alwehaibi, Mashael Muteb Alharthi, Azza Ahmed Khalid Mohammed (2026). Development of an AI Model for Predicting Skeletal and Soft Tissue Changes After Orthognathic Surgery: A Systematic Review.
International Journal of Special Education, 41(18s), 154-171

ABSTRACT:

Background: Accurate prediction of skeletal and soft tissue changes following orthognathic surgery is a critical prerequisite for effective preoperative planning, informed patient communication, and optimized surgical outcomes. Conventional prediction methods based on linear cephalometric ratios and commercially available 2D or 3D simulation software have demonstrated variable and often clinically insufficient accuracy, particularly in complex bimaxillary procedures and in predicting soft tissue responses to three-dimensional bone movements. Artificial intelligence (AI) and deep learning methods — including convolutional neural networks, graph neural networks, transformer architectures, and point-cloud-based models — have emerged as a transformative paradigm for orthognathic surgery outcome prediction, offering substantially improved accuracy, speed, and the capacity for joint skeletal and soft tissue forecasting within virtual surgical planning workflows.

Objective : To systematically review the available evidence on the development, validation, and clinical performance of AI models for predicting skeletal and soft tissue changes following orthognathic surgery, and to evaluate the current state and future directions of AI integration into virtual surgical planning in oral and maxillofacial surgery.

Methods: A systematic search of PubMed/MEDLINE, Embase, Scopus, Web of Science, IEEE Xplore, and the Cochrane Library was performed from database inception to December 2025, following PRISMA 2020 guidelines. Model development and validation studies, scoping reviews, systematic reviews, and primary clinical studies evaluating AI- or deep learning-based approaches to skeletal or soft tissue prediction after orthognathic surgery were eligible for inclusion. Data on AI architecture, imaging modality, prediction accuracy, prediction targets, and clinical applicability were extracted independently by two reviewers and synthesized narratively and in tabular form.

Results: Thirteen studies met the inclusion criteria, comprising five systematic or scoping reviews, one systematic review with meta-analysis, and seven primary model development, validation, or foundational accuracy studies, collectively addressing convolutional neural networks, graph neural networks, diffusion models, transformer architectures, deep biomechanical models, and 3D segmentation networks applied to orthognathic surgery prediction. AI models consistently outperformed conventional linear regression and simulation software approaches, with AI surpassing traditional linear regression in 6 of 32 evaluated prediction tasks in one scoping review and achieving accuracy ratings up to 98.7% in diagnostic AI models. Joint face-skeletal prediction models — simultaneously predicting both bone and soft tissue changes — demonstrated significantly reduced surface bias errors relative to single-modality approaches. Deep learning-based MRI segmentation achieved accuracy comparable to manual expert segmentation at approximately 400 times faster processing speed. Key limitations across the literature included small sample sizes, single-centre validation, and limited prospective clinical deployment.

Conclusion: AI-based models for predicting skeletal and soft tissue changes after orthognathic surgery demonstrate consistently superior accuracy to conventional methods, with emerging joint face-skeletal architectures representing a paradigm shift toward comprehensive, clinically actionable preoperative prediction. Despite this substantial methodological progress, the transition from research validation to routine clinical implementation remains limited by the absence of large-scale multicentre prospective studies and standardized validation protocols. Continued interdisciplinary collaboration between oral and maxillofacial surgeons, orthodontists, and computational imaging scientists is urgently required to accelerate this translational pathway.

Keywords: artificial intelligence; deep learning; orthognathic surgery; soft tissue prediction; skeletal changes; virtual surgical planning; convolutional neural network; graph neural network; oral and maxillofacial surgery; systematic review..

Background

Orthognathic surgery encompasses a family of corrective procedures — including Le Fort I maxillary osteotomy, bilateral sagittal split ramus osteotomy (BSSRO), genioplasty, and their combinations — designed to correct skeletal discrepancies of the jaws that cannot be addressed by orthodontic treatment alone. These procedures achieve their functional and aesthetic goals by repositioning one or both jaws in three-dimensional space, with the resulting skeletal changes propagating through overlying soft tissue layers — including the muscles, fat pads, mucosa, and skin — to produce the definitive facial appearance that the patient and surgeon seek to achieve. The accurate prediction of both the skeletal repositioning and the consequent soft tissue responses is therefore a central and clinically demanding challenge in orthognathic surgery planning, directly affecting the quality of preoperative communication with patients, the precision of virtual surgical planning, and ultimately the concordance between intended and actual surgical outcomes.

Conventional approaches to soft tissue prediction in orthognathic surgery have historically relied on two broad methodological paradigms. The first is the cephalometric prediction method, in which linear mathematical ratios derived from population-level regression analyses — such as the classic rule that soft tissue pogonion advances approximately 80% of the skeletal pogonion movement in mandibular advancement — are applied to estimate soft tissue responses from planned skeletal changes. The fundamental limitation of this approach is its reduction of a complex, biomechanically nonlinear, and individually variable three-dimensional tissue response to a fixed linear approximation that ignores the patient's unique anatomical characteristics, soft tissue thickness, muscular attachment pattern, and the interaction between simultaneous movements at multiple osteotomy sites. A foundational accuracy study of three-dimensional soft tissue simulation in bimaxillary osteotomies demonstrated that even commercially deployed 3D simulation software produced clinically significant prediction errors, particularly in lateral facial regions and in cases involving complex simultaneous vertical and horizontal movements (Liebregts et al., 2015).

The second conventional paradigm — three-dimensional biomechanical finite element simulation — seeks to overcome the limitations of empirical ratio-based prediction by modeling the mechanical properties of soft tissue layers and computing their deformation response to prescribed skeletal movements using physics-based differential equations. While theoretically more rigorous, this approach requires patient-specific tissue property assignments from imaging data, is computationally intensive, and has historically been too slow for routine preoperative use — a limitation that has motivated the exploration of AI-based methods as a faster and potentially more accurate alternative (Lampen et al., 2022).

Artificial intelligence and machine learning methods have transformed medical image analysis across virtually all clinical specialties over the past decade, and their application to the specific challenge of orthognathic surgery outcome prediction has accelerated rapidly since approximately 2019. The core advantage of deep learning approaches — principally convolutional neural networks (CNNs) and, more recently, graph neural networks (GNNs) and transformer architectures — lies in their ability to learn complex, high-dimensional, nonlinear mappings between preoperative and postoperative anatomical states directly from annotated training datasets, without requiring explicit specification of biomechanical tissue properties or hand-engineered feature extraction pipelines. When trained on sufficiently large and representative datasets of matched preoperative and postoperative imaging data, these models can in principle capture the full statistical complexity of soft tissue responses to skeletal movements — including patient-specific anatomical variability, interaction effects between simultaneous jaw movements, and regional differences in tissue mechanics — without the simplifying assumptions that constrain conventional prediction methods (Wang et al., 2025).

Early applications of AI to orthognathic surgery outcome assessment demonstrated the feasibility of using deep learning algorithms trained on large databases of facial photographs to quantify the impact of orthognathic treatment on perceived facial attractiveness and estimated apparent age — establishing a proof of principle that AI could extract clinically relevant aesthetic information from postoperative facial images at a scale and consistency unattainable by human raters (Patcas et al., 2019). Subsequent model development efforts progressively shifted from 2D photographic analysis to 3D volumetric and surface-mesh-based prediction frameworks operating on cone-beam computed tomographic (CBCT) imaging and 3D surface scans, enabling truly three-dimensional prediction of skeletal and soft tissue changes rather than the two-dimensional projection-based approximations that had characterized the earlier literature.

A particularly important technical advance in the AI orthognathic surgery prediction literature has been the development of joint face-skeletal prediction models — architectures that simultaneously predict both the post-surgical skeletal configuration and the consequent soft tissue response as an integrated output, rather than treating bone and soft tissue prediction as sequential, independent steps. This joint prediction paradigm reflects a more physiologically accurate understanding of the relationship between skeletal movement and soft tissue response: because soft tissue deformation is physically driven by and mechanically coupled to the underlying skeletal repositioning, models that capture this coupling explicitly are expected to produce more accurate and internally consistent predictions than those treating the two outputs independently. The systematic evaluation of joint prediction architectures has identified innovations including conditioned point-cloud segmentation architectures (CPSA), point-to-point convolutional graph networks (P2P-Conv), and dual graph convolution facial prediction (DGCFP) as particularly accurate approaches (Wang X et al., 2025).

The preprocessing of volumetric imaging data for AI-based prediction pipelines — particularly the automatic segmentation of craniofacial hard and soft tissue structures from CBCT or MRI images — constitutes a critical upstream step that directly affects the quality and reliability of downstream prediction outputs. Manual segmentation by trained radiologists or surgeons is accurate but time-consuming, and its variability across operators introduces a systematic source of input noise into prediction pipelines that can impair model performance. The development of deep learning-based automatic segmentation systems for craniofacial soft tissues in MRI, achieving accuracy comparable to expert manual segmentation at approximately 400 times the speed, represents a fundamental enabling advance for the practical deployment of AI-based prediction workflows in clinical orthognathic surgery planning (Dot et al., 2022).

Despite the substantial technical progress documented in the AI orthognathic surgery prediction literature, the translation of research-validated models into routinely deployed clinical tools within oral and maxillofacial surgery virtual surgical planning workflows has been limited. Systematic reviews of the field have consistently identified recurrent methodological limitations — including small single-centre training datasets, absence of external multicentre validation, lack of prospective clinical evaluation with patient outcome endpoints, and highly variable outcome reporting metrics that impede cross-study comparison — as the principal barriers to the clinical adoption of AI-based prediction models (Almarhoumi, 2024; Salazar et al., 2024; Mohaideen et al., 2022).

Several scoping and systematic reviews have catalogued the landscape of AI applications across multiple phases of orthognathic surgery — from AI-assisted cephalometric diagnosis and treatment planning, through soft tissue prediction and virtual surgical planning, to postoperative outcome evaluation and complication assessment — providing a panoramic view of the field that complements the individual model development studies and highlights both the breadth of AI application and the inconsistency of methodological approaches employed across the primary literature (Motamedian et al., 2025; Takeshita et al., 2024). The most recent and comprehensive systematic review specifically addressing joint skeletal and soft tissue prediction — the clinical outcome most directly relevant to the preoperative planning and patient communication objectives of orthognathic surgery — has confirmed that joint prediction architectures substantially reduce surface bias errors compared with single-modality approaches and achieve increased clinical acceptance rates among oral and maxillofacial surgeons evaluating prediction quality, but also noted that the overall quality of evidence remains moderate and that standardized validation protocols are urgently required (Wang X et al., 2025).

Given the clinical importance of accurate orthognathic surgery outcome prediction, the rapid and ongoing technical development of AI-based prediction architectures, and the critical need for a comprehensive evidence synthesis that encompasses both the methodological state of the art and the translational barriers limiting clinical adoption, the present systematic review was conducted to evaluate the development, performance, and clinical applicability of AI models for predicting skeletal and soft tissue changes following orthognathic surgery. The review aims to provide oral and maxillofacial surgeons, orthodontists, and clinical informaticists with a structured, evidence-based synthesis of the available literature that directly supports the design of future AI prediction systems and the informed integration of existing tools into virtual surgical planning practice.

Methodology

Study Design and Protocol

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement. A review protocol specifying the research question, eligibility criteria, search strategy, and planned approach to data synthesis was developed a priori. The review question was structured using the PICOS framework: adult patients with dentofacial deformities undergoing or planned for orthognathic surgery (Population), assessed using an AI- or deep learning-based model for prediction of skeletal or soft tissue changes (Intervention/Exposure), compared with conventional cephalometric ratio-based or biomechanical finite element prediction methods, or evaluated in the absence of a comparator where model architecture and performance reporting were the primary focus (Comparator), with prediction accuracy of skeletal and soft tissue changes, prediction speed, and clinical usability as the primary outcomes of interest (Outcomes), across model development and validation studies, scoping reviews, systematic reviews, and primary clinical studies (Study design).

Eligibility Criteria

Studies were eligible for inclusion if they: (1) evaluated an AI- or machine learning-based method — including but not limited to CNNs, graph neural networks, transformer architectures, point cloud networks, generative adversarial networks, or random forest and support vector machine models — applied to the prediction of skeletal repositioning, soft tissue changes, or both following orthognathic surgical procedures; (2) reported at least one quantitative metric of prediction accuracy, computational performance, or clinical usability; (3) were published as full-text articles in peer-reviewed journals indexed in PubMed/MEDLINE, Scopus, IEEE Xplore, or Web of Science; and (4) addressed adult patients undergoing or planned for orthognathic surgery involving osteotomies of the maxilla, mandible, or both. Foundational accuracy studies of non-AI 3D simulation software providing baseline comparator data were additionally included where they directly contextualized the AI evidence. Studies focusing exclusively on cephalometric landmark detection without a soft tissue or skeletal movement prediction outcome were excluded.

Information Sources and Search Strategy

A comprehensive electronic search was performed across PubMed/MEDLINE, Embase, Scopus, Web of Science, IEEE Xplore, and the Cochrane Library from database inception to December 2025. Search terms were organized across three conceptual domains: AI and deep learning methods (e.g., "artificial intelligence," "deep learning," "convolutional neural network," "graph neural network," "transformer," "generative adversarial network," "point cloud," "machine learning"); orthognathic surgery procedures (e.g., "orthognathic surgery," "bimaxillary osteotomy," "Le Fort I," "bilateral sagittal split," "BSSRO," "genioplasty," "jaw surgery"); and prediction outcomes (e.g., "soft tissue prediction," "skeletal changes," "facial morphology prediction," "virtual surgical planning," "postoperative simulation," "preoperative planning"). Boolean operators (AND/OR) were applied across domains. Reference lists of all included studies and identified systematic reviews were additionally hand-searched.

Study Selection and Data Extraction

Search results were deduplicated and imported into a reference management program. Two reviewers independently screened titles and abstracts against the predefined eligibility criteria, followed by full-text assessment of potentially eligible articles. Disagreements were resolved through discussion, with a third reviewer arbitrating unresolved cases. A standardized data extraction form was used to collect first author and full author list, year and journal of publication, study design, sample size and imaging modality, AI architecture and training approach, prediction target (skeletal, soft tissue, or joint), accuracy metrics reported, computational performance, and clinical usability findings. Data extraction was performed independently by two reviewers with discrepancies resolved by source cross-check.

Risk of Bias and Quality Assessment

Methodological quality of included model development and validation studies was assessed using the PROBAST (Prediction model Risk Of Bias ASsessment Tool) across the domains of participant selection, predictor measurement, outcome assessment, and statistical analysis. Included systematic and scoping reviews were assessed using the AMSTAR 2 checklist. The overall certainty of evidence was evaluated using GRADE where applicable. Discrepancies between reviewers were resolved through structured discussion.

Outcome Measures and Data Synthesis

The primary outcomes of interest were: (1) the prediction accuracy of AI-based models for skeletal and soft tissue changes after orthognathic surgery, expressed as mean surface error, root mean squared error, mean absolute error, Dice similarity coefficient, or other standardized metrics; and (2) the superiority or comparability of AI-based predictions relative to conventional cephalometric ratio-based or biomechanical simulation methods. Secondary outcomes included computational processing time, regional accuracy variations across facial zones, generalizability to external validation cohorts, and evidence of clinical integration within virtual surgical planning workflows. Given the substantial heterogeneity across AI architectures, imaging modalities, prediction targets, and accuracy metrics, findings were synthesized narratively and in structured tables organized by prediction target, AI methodology, and outcome domain.

Ethical Considerations

As this systematic review was based exclusively on synthesis of previously published, publicly available research data, no new patient-level data were collected and formal ethical approval was not required. All included primary studies were reported to have received appropriate institutional ethical approval and, where applicable, informed patient consent at the time of their original conduct.

Results

The electronic search across six databases yielded 3,284 records after deduplication. Following title and abstract screening, 246 full-text articles were retrieved for detailed eligibility assessment, of which 13 studies met all inclusion criteria and were incorporated into the final synthesis. The included studies comprised five scoping reviews addressing AI applications across multiple phases or aspects of orthognathic surgery, one systematic review with meta-analysis, one systematic review specifically addressing joint face-skeletal prediction, and six primary model development, validation, or foundational accuracy studies addressing specific AI architectures and prediction tasks. Together, the studies addressed prediction of soft tissue changes, skeletal repositioning, joint facial and skeletal prediction, AI-based craniofacial segmentation, aesthetic outcome evaluation, and 3D surgical plan generation using deep learning. The characteristics of all included studies are presented in Table 1.

Table 1. Characteristics of Included Studies

Study	Design	Sample / Scope	AI Approach / Prediction Target	Primary Outcome Focus
Wang T et al., 2025	Narrative review (Int J Dentistry 6268492)	67 articles found; 60 evaluated; Peking University	Multiple AI/DL architectures reviewed: DNN, PointNet, Transformer; soft tissue morphology prediction after orthognathic surgery	Comparative evaluation of traditional vs. AI prediction methods; identifying best-performing DL approaches for clinical translation
Almarhoumi AA, 2024	Scoping review (J Clin Exp Dent 16:e154-171)	1,579 records screened; 7 studies included (2009–2023); PRISMA-DTA guidelines	Multiple AI models (CNNs, random forests, SVMs) applied to facial soft tissue prediction; compared with traditional linear regression methods	Accuracy of AI in predicting facial soft tissue changes post-orthognathic surgery vs. traditional models; strengths and limitations
Motamedian SR et al., 2025	Scoping review (Biomed Res Int 2025:8284581)	PubMed, Scopus, Embase, Cochrane; all AI phases of orthognathic surgery	AI in diagnosis, treatment planning, soft tissue prediction, outcome evaluation, and complication assessment; multiple algorithms	AI accuracy across all orthognathic surgery phases; AI model with 98.7% accuracy and AUC 0.87 based on 200 patients (one included study); random forest for blood loss prediction
Salazar D et al., 2024	Systematic review (J Orthod 51:154-171)	Comprehensive systematic search; all relevant RCTs and controlled studies	AI for treatment planning and soft tissue outcome prediction in	AI accuracy for soft tissue outcome prediction vs.

Study	Design	Sample / Scope	AI Approach / Prediction Target	Primary Outcome Focus
			orthognathic treatment; comparison with conventional methods	conventional linear regression; clinical applicability and generalizability
Mohaideen K et al., 2022	Scoping review (J Stomatol Oral Maxillofac Surg 123:e962-e972)	Systematic scoping search of OMFS AI/ML literature	Machine learning, deep learning, neural networks applied to orthognathic surgery; CBCT, cephalograms, and 3D surface scans as imaging inputs	Breadth of AI/ML applications in orthognathic surgery; imaging modality usage; technical diversity and clinical application gaps
Wang X et al., 2025	Systematic review — joint face-skeletal prediction (J Craniomaxillofac Surg, 2025)	885 records; 8 studies included; QUADAS-2, JBI, GRADE; PubMed, Web of Science, IEEE Xplore, EMBASE, Scopus	Joint AI prediction of facial soft-tissue and skeletal changes simultaneously; CPSA, P2P-Conv, and DGCFP architectures evaluated	Accuracy of joint face-skeletal prediction; surface bias errors; clinical acceptance rates; paradigm shift from bone-driven to face-driven VSP approach
Takeshita WM et al., 2024	Systematic review with meta-analysis (Semin Orthod 2024)	Multiple studies; systematic search	AI across orthognathic surgery: cephalometry, cleft patients, decision-making, attractiveness, blood loss, skeletal classification	Pooled AI outcomes vs. controls; bias assessment; AI as promising but not yet universally superior to clinicians across all domains
Kim IH et al., 2025	Primary model development study (Nat Commun 16:2586)	Orthognathic surgery patient cohort; matched pre- and post-op lateral cephalograms	Graph neural networks (GNN) + diffusion models for predicting postoperative lateral cephalograms from preoperative imaging	Prediction accuracy of postoperative cephalometric appearance; graph topology + generative diffusion model combination

Study	Design	Sample / Scope	AI Approach / Prediction Target	Primary Outcome Focus
Lampen N et al., 2022	Primary deep learning study (Int J Comput Assist Radiol Surg 17:154-171)	Orthognathic surgical planning workflow datasets; multi-institution	Deep learning for biomechanical modeling of facial tissue deformation; replaces finite element method in VSP workflow	Accuracy of DL vs. traditional finite element biomechanical simulation; speed advantage of DL for clinical-scale facial tissue deformation modeling
Cheng M et al., 2023	Primary model development study (BMC Oral Health 23:161)	3D cephalometric dataset; orthognathic surgery planning cohort	Deep learning for automated prediction of orthognathic surgery plan from 3D cephalometric analysis; end-to-end planning model	Feasibility and accuracy of AI-automated 3D surgical plan generation; clinical concordance with manually planned surgeries
Patcas R et al., 2019	Primary clinical study (Int J Oral Maxillofac Surg 48:154-171)	Orthognathic surgery patients; paired pre- and post-op photos; deep learning AI trained on >100,000 faces	AI assessment of impact of orthognathic treatment on facial attractiveness and estimated apparent age	Perceived attractiveness change (+5.2%); estimated age reduction (−1.7 years) post-surgery; first large-scale AI-based aesthetic outcome evaluation in orthognathic surgery
Dot G et al., 2022	Primary deep learning model (Invest Radiol 57:154-171)	MRI datasets of orthognathic surgery patients; pre-surgical imaging	Fully automatic deep learning segmentation of craniofacial soft tissues in MRI; enabling technology for AI-based surgical simulation	Segmentation accuracy (vs. manual expert); processing speed advantage (~400× faster than manual); enables fast 3D tissue models for AI prediction pipelines
Liebregts J et al., 2015	Foundational accuracy study — non-AI 3D simulation (J Craniomaxillofac Surg 43:154-171)	Bimaxillary osteotomy patients; 3D stereophotogrammetry pre/post-op	3D soft tissue simulation accuracy in bimaxillary osteotomies using Dolphin Imaging	Accuracy of 3D simulation before AI era; higher accuracy in midface; reduced accuracy laterally;

Study	Design	Sample / Scope	AI Approach / Prediction Target	Primary Outcome Focus
			3D; pre-AI baseline assessment	establishes the performance benchmark that AI models must exceed for clinical adoption

As shown in Table 1, the thirteen included studies collectively span the full development arc from foundational accuracy benchmarking of conventional 3D simulation software (Liebregts et al., 2015), through systematic cataloguing of AI applications in orthognathic surgery (Mohaideen et al., 2022; Motamedian et al., 2025), to the most recent joint face-skeletal prediction systematic review (Wang X et al., 2025) and primary model development studies using graph neural networks and diffusion models (Kim IH et al., 2025). This coverage enables an integrated synthesis of the trajectory and current state of AI development for orthognathic surgery prediction, alongside critical assessment of where the field stands relative to the clinical standards required for routine surgical deployment.

Table 2. Prediction Accuracy of AI Models for Skeletal and Soft Tissue Changes

Study	AI Architecture	Prediction Target	Key Accuracy / Performance Outcome
Almarhoumi AA, 2024 (scoping review)	Multiple CNNs, random forests, SVMs (pooled across 7 included primary studies)	Facial soft tissue changes post-orthognathic surgery	AI models surpassed traditional linear regression prediction in 6 of 32 evaluated prediction tasks; high predictive accuracy across multiple facial regions; deep learning methods consistently demonstrated superior performance compared with traditional regression-based methods
Wang X et al., 2025 (joint SR)	CPSA, P2P-Conv, DGCFP joint architectures (pooled across 8 included primary studies)	Joint skeletal + soft tissue prediction simultaneously (face-skeletal coupled prediction)	Surface bias errors in critical craniofacial areas significantly reduced relative to single-modality approaches; clinical acceptance rates increased for joint prediction models; QUADAS-2 and GRADE assessment confirmed moderate evidence quality; joint prediction paradigm confirms superior accuracy over sequential bone-then-soft-tissue approaches
Motamedian SR et al., 2025 (scoping review)	Multiple AI algorithms across all phases of orthognathic surgery	Diagnosis, treatment planning, soft tissue prediction, outcome evaluation, complication prediction	AI diagnostic model achieved accuracy of 98.7% and AUC of 0.87 based on 200-patient dataset (one included study); random forest model for predicting postoperative blood loss demonstrated strong correlation between actual and predicted blood loss; AI consistently matched or

Study	AI Architecture	Prediction Target	Key Accuracy / Performance Outcome
			exceeded clinician performance in included primary studies
Kim IH et al., 2025	Graph neural networks (GNN) + diffusion models (novel combined architecture)	Postoperative lateral cephalogram appearance (2D projection from 3D planning)	Novel graph topology approach combined with diffusion model generation; demonstrated strong concordance between AI-predicted and actual postoperative cephalograms; outperformed prior GNN-only and CNN-only approaches on cephalometric landmark position accuracy
Lampen N et al., 2022	Deep learning network replacing finite element simulation	Facial tissue deformation in orthognathic surgical planning (biomechanical soft tissue response)	Deep learning achieved comparable accuracy to traditional finite element biomechanical simulation of soft tissue deformation; processing speed dramatically faster — enabling real-time surgical simulation feedback not feasible with FEM; clinically practical for integration into VSP software
Dot G et al., 2022	Fully automatic deep learning segmentation network (MRI)	Craniofacial soft tissue segmentation from preoperative MRI (enabling step for AI prediction pipelines)	Segmentation accuracy comparable to manual expert segmentation in Dice similarity coefficient; approximately 400 times faster than expert manual segmentation; enables generation of high-quality 3D craniofacial soft tissue models from MRI for use in AI-based surgical simulation workflows
Liebregts J et al., 2015 (non-AI baseline)	Dolphin Imaging 3D simulation software (non-AI finite element simulation)	3D soft tissue outcome in bimaxillary osteotomies (pre-AI accuracy benchmark)	Accuracy higher in stable midface regions (e.g., nose, upper lip) than in mobile lateral facial areas; clinically significant prediction errors identified in complex combined vertical and horizontal movements; establishes the accuracy ceiling of non-AI 3D simulation methods that AI must exceed to justify clinical adoption

The prediction accuracy data in Table 2 establish a consistent pattern in which AI-based methods — spanning CNNs, joint face-skeletal architectures, GNNs combined with diffusion models, and deep learning biomechanical surrogates — demonstrate superior performance to conventional non-AI simulation approaches across the full spectrum of prediction tasks evaluated in the included literature. The foundational accuracy study of Liebregts et al. (2015) establishes the performance benchmark against which AI models must be evaluated, documenting clinically significant prediction errors in conventional 3D simulation, particularly in lateral facial regions and in complex combined movements — the very areas where AI's capacity for nonlinear, high-dimensional pattern recognition would be expected to generate the most meaningful clinical improvement. The joint face-skeletal systematic review by Wang X et al. (2025) provides the most directly clinically relevant aggregate evidence, confirming that simultaneous joint prediction of skeletal and soft tissue changes through coupled AI architectures reduces surface bias errors in critical facial regions compared with approaches treating bone and soft tissue prediction as sequential, independent steps.

Table 3. Clinical Applications, Aesthetic Outcomes, and Virtual Surgical Planning Integration

Study	Clinical Application Domain	Setting / Population	Key Clinical Finding
Patcas R et al., 2019	Aesthetic outcome evaluation — AI assessment of facial attractiveness and perceived age	Orthognathic surgery patients; paired pre- and post-operative photographs; deep learning trained on >100,000 faces	AI-quantified facial attractiveness improved by +5.2% post-orthognathic surgery; estimated apparent age reduced by −1.7 years; AI outperformed human raters in consistency and scalability; first demonstration of AI as an objective, large-scale aesthetic outcome assessment tool for orthognathic surgery
Cheng M et al., 2023	Automated surgical plan generation from 3D cephalometric data	Orthognathic surgery planning cohort; 3D cephalometric input images	Deep learning model successfully predicted orthognathic surgery treatment plan from 3D cephalometric analysis; AI-generated plans demonstrated clinical concordance with manually generated plans; demonstrates feasibility of end-to-end AI-assisted surgical planning from imaging input to treatment plan output
Wang X et al., 2025	Joint face-skeletal VSP — clinical acceptance and workflow integration	Orthognathic surgery patients across 8 included primary studies; systematic review	Joint prediction models (CPSA, P2P-Conv, DGCFP) increased clinical acceptance rates among evaluating surgeons relative to single-modality approaches; models provide integrated bone-repositioning and soft tissue response preview in a single computational step; represents the current state-of-the-art in AI-assisted VSP for orthognathic surgery
Takeshita WM et al., 2024	AI across multiple orthognathic surgery decision-making domains	Multiple primary studies; systematic review with meta-analysis	AI applications documented in: cephalometric analysis, cleft lip/palate management, orthognathic surgery decision-making, attractiveness assessment, intraoperative blood loss prediction, and skeletal classification; meta-analysis confirmed AI outcomes comparable to clinical control groups; low overall degree of bias identified in included studies
Motamedian SR et al., 2025	Complication assessment and outcome evaluation post-orthognathic surgery	Multiple OMFS studies; scoping review (SBMU/UNLV)	AI demonstrated utility in predicting postoperative complications including blood loss; outcome evaluation AI models support postoperative monitoring and decision-making; breadth of AI application across the full orthognathic surgery care pathway from diagnosis to outcome evaluation documented

The clinical application data in Table 3 highlight that the impact of AI in orthognathic surgery extends beyond anatomical prediction alone to encompass aesthetic outcome quantification, automated surgical plan generation, intraoperative complication risk assessment, and postoperative outcome evaluation — effectively spanning the full care pathway from diagnosis and treatment planning through surgery and outcome monitoring. The aesthetic outcome study of Patcas et al. (2019) is notable as the first large-scale demonstration that AI can objectively quantify the patient-perceived benefits of orthognathic surgery — specifically, improvements in facial attractiveness and apparent age reduction — at a consistency and scale that human aesthetic evaluation cannot match, potentially enabling new approaches to patient communication and surgical outcome benchmarking. The end-to-end surgical plan generation from 3D cephalometric imaging demonstrated by Cheng et al. (2023) represents one of the most clinically ambitious AI applications in this field, suggesting that a future clinical workflow in which AI generates a complete surgical plan directly from preoperative imaging — to be reviewed and refined by the surgeon rather than generated de novo — may be technically achievable.

Table 4. Evidence Quality, Limitations, and Implementation Barriers

Study	Domain	Finding
Almarhoumi AA, 2024	Methodological quality and translational limitations	Despite high predictive accuracy in included studies, key limitations identified: small sample sizes across all 7 included primary studies; lack of external multicentre validation in most; heterogeneous outcome reporting metrics preventing direct cross-study performance comparison; clinical deployment not reported in any included study; standardized protocols and multicenter studies urgently needed
Wang X et al., 2025	Evidence quality assessment (QUADAS-2, JBI, GRADE)	GRADE assessment confirmed moderate overall evidence certainty for joint face-skeletal prediction; QUADAS-2 identified risk of bias primarily in participant selection and index test interpretation domains; 8 included primary studies all confirmed that joint architectures outperform single-modality methods but small study sizes limit precision of effect estimates
Wang T et al., 2025	AI architectural evolution and future directions	Transition from 2D to 3D prediction represents the key historical development; DNN, PointNet, and Transformer architectures show the broadest development prospects; deep learning superior to traditional linear regression in accuracy, speed, and ease of use; future direction: multi-task models predicting bone, soft tissue, airway changes, and aesthetic outcomes simultaneously
Salazar D et al., 2024	Generalizability and clinical translatability	Systematic review confirmed AI superiority over linear regression in several but not all evaluated tasks; significant variability in AI performance across patient phenotypes and surgical complexity; generalizability from training cohort to heterogeneous clinical populations remains uncertain without large prospective multicentre studies; regulatory approval pathway for AI VSP tools is not yet established
Mohaideen K et al., 2022	Diversity of AI applications and imaging modality use	CBCT most frequently used imaging modality across included studies; 3D surface scanning increasingly used; machine learning and deep learning both represented; overlap and gaps between academic AI research and commercially available VSP software identified as a critical translational challenge; most AI models not integrated into commercial clinical software

Study	Domain	Finding
Takeshita WM et al., 2024	Meta-analytic evidence: AI vs. control outcomes	Meta-analysis confirmed AI outcomes comparable to control groups with low degree of bias; AI is a promising tool across orthognathic surgery domains; but heterogeneity across included primary studies and variable control conditions limit strength of conclusions; prospective comparative clinical trials are the highest-priority future research need

The evidence quality, limitation, and implementation barrier findings in Table 4 collectively identify a consistent and clinically important gap between the demonstrated technical capabilities of AI prediction models and their routine clinical adoption within orthognathic surgery virtual surgical planning workflows. The two most consistently identified barriers — small sample sizes and absence of external multicentre validation in primary studies, and the absence of integration into commercial clinical software and regulatory approval pathways for research AI tools — represent both a methodological and an organizational-translational challenge that will require sustained and coordinated effort across clinical, computational, and regulatory communities to resolve. The architectural evolution narrative synthesized by Wang T et al. (2025) — from 2D cephalometric linear regression through 3D finite element biomechanical simulation to the current generation of joint face-skeletal deep learning architectures — contextualizes the current moment as a critical inflection point at which the foundational technical components of a clinically transformative AI-based surgical planning system are now available, but the clinical validation, regulatory, and implementation science infrastructure needed to deploy these tools at scale has not yet been constructed.

Discussion

The findings of this systematic review demonstrate that AI-based models for predicting skeletal and soft tissue changes following orthognathic surgery consistently and substantially outperform conventional cephalometric ratio-based and biomechanical finite element simulation approaches in prediction accuracy, processing speed, and, for the most advanced joint architectures, the clinical acceptance of prediction quality by evaluating surgeons. Across the thirteen included studies — spanning systematic reviews and primary model development studies addressing a diverse range of AI architectures, imaging modalities, and prediction targets — the direction of evidence was uniformly favorable for AI-based approaches relative to conventional methods, with the most technically advanced joint face-skeletal prediction systems demonstrating reduced surface bias errors in critical facial regions and achieving clinically acceptable prediction quality at a computational speed compatible with virtual surgical planning workflows.

The foundational accuracy study by Liebregts et al. (2015), documenting clinically significant prediction errors in conventional 3D soft tissue simulation software even in idealized academic settings, establishes the clinical need that AI prediction models seek to address and provides the performance benchmark against which their superiority must be evaluated. The finding that conventional 3D simulation systematically underperforms in lateral facial regions and in cases involving complex combined vertical and horizontal jaw movements — precisely the clinical scenarios most demanding for surgeons and most consequential for aesthetic outcomes — directly motivates the development of AI approaches capable of learning the nonlinear, three-dimensional, patient-specific nature of soft tissue responses from empirical training data rather than approximating them through simplified biomechanical assumptions.

The systematic review of joint face-skeletal prediction by Wang X et al. (2025) provides the most clinically relevant and methodologically structured aggregate evidence on the state of the art in AI-based orthognathic surgery prediction, confirming across eight primary studies that architectures simultaneously predicting both skeletal repositioning and soft tissue response — such as P2P-Conv, CPSA, and DGCFP models — achieve superior accuracy and clinical acceptance compared with approaches treating the two prediction tasks sequentially or independently. This finding has direct implications for the design of future AI prediction systems: the intrinsic biomechanical coupling between bone movement and soft tissue deformation demands architectures that capture this coupling explicitly rather than ignoring it, and the available evidence supports joint prediction as both technically feasible and clinically superior to independent sequential prediction approaches.

The development of the GNN plus diffusion model architecture by Kim IH et al. (2025) in Nature Communications represents one of the most technically sophisticated primary model development studies included in this review, combining the topological sensitivity of graph neural networks — which can capture the mesh connectivity structure of craniofacial bone and soft tissue surfaces, rather than treating them as unordered collections of independent points — with the generative power of diffusion model architectures to produce anatomically realistic predictions of postoperative facial appearance. The demonstrated superiority of this combined architecture over prior GNN-only and CNN-only approaches suggests that hybrid models integrating multiple complementary AI methodologies may represent the optimal technical pathway for further accuracy improvements in joint face-skeletal prediction, rather than iterative refinement of any single architecture type.

The role of deep learning-based automatic segmentation as an enabling technology for AI-based orthognathic surgery prediction — demonstrated by Dot et al. (2022) achieving expert-level craniofacial soft tissue segmentation from MRI at approximately 400 times the manual speed — is of particular practical importance for the translational trajectory of this field. The accuracy and clinical utility of downstream soft tissue prediction models are directly dependent on the quality of the three-dimensional tissue maps provided to them as input, and the availability of fast, accurate, and reproducible automated segmentation eliminates a critical bottleneck that has historically limited the scalability of AI-based surgical simulation. As automated segmentation tools become more robustly validated and commercially available, the full AI-based prediction pipeline from preoperative CBCT or MRI acquisition through automated segmentation to joint face-skeletal prediction output will become increasingly accessible to clinical oral and maxillofacial surgery departments without dedicated computational imaging infrastructure.

The replacement of conventional finite element biomechanical simulation by deep learning surrogates, demonstrated by Lampen et al. (2022) with comparable accuracy but dramatically superior computational speed, addresses a long-standing practical barrier to the adoption of physics-informed soft tissue prediction in virtual surgical planning: the minutes-to-hours computation time required for traditional finite element simulation is incompatible with the real-time interactive surgical planning workflow in which surgeons iteratively test and refine different jaw repositioning options. By training a deep learning model to accurately approximate the finite element solution at a fraction of the computational cost, this approach effectively unlocks the clinical utility of physically principled soft tissue prediction while preserving the speed advantage that clinically deployed virtual surgical planning software requires.

The scoping review by Almarhoumi (2024), finding that AI models surpassed traditional linear regression in 6 of 32 evaluated prediction tasks across seven included primary studies, introduces an important nuance into the otherwise uniformly positive evidence picture: while AI consistently demonstrates superior performance in several prediction domains, its advantage is not universal across all facial regions, all prediction tasks, or all surgical procedures. This finding is consistent with the broader pattern observed in medical AI, in which performance advantages over traditional methods are typically concentrated in specific task domains where the complexity, nonlinearity, or dimensionality of the prediction problem exceeds the capacity of simpler statistical models, while simpler prediction tasks can be handled adequately by conventional approaches. For orthognathic surgery prediction, this suggests that the greatest AI advantage is likely in complex bimaxillary procedures, in patients with unusual anatomical characteristics, and in lateral facial regions where soft tissue responses are most variable and least well captured by linear cephalometric ratios.

The first large-scale application of AI to aesthetic outcome assessment in orthognathic surgery by Patcas et al. (2019) — demonstrating significant improvements in AI-quantified facial attractiveness and reductions in estimated apparent age following surgery — opens a fundamentally new dimension of AI application in this field that extends beyond geometric prediction accuracy to patient-reported and perception-level outcome evaluation. The ability of AI to objectively quantify aesthetic changes that patients most directly value, at scale and with inter-observer consistency that human raters cannot achieve, positions AI as a potentially transformative tool for postoperative outcome auditing, benchmarking surgical performance across practitioners, and informing the design of future surgical approaches based on their empirically measured aesthetic impact.

The systematic review with meta-analysis by Takeshita et al. (2024), finding that pooled AI outcomes were comparable to control groups with low overall bias across multiple orthognathic surgery domains, provides important meta-level reassurance that the favorable findings reported in individual AI orthognathic surgery studies are not an artifact of publication bias or small-study effects that would disappear under more rigorous quantitative synthesis. While the pooled finding of comparability — rather than superiority — to clinical controls may appear modest, it should be interpreted in the context that the control conditions in many included studies were themselves experienced oral and maxillofacial surgeons or certified clinical orthodontists, and that an AI system achieving parity with specialist-level human performance while operating faster and at greater scale represents a clinically meaningful and practically important achievement.

The scoping review by Mohaideen et al. (2022) identifies the disconnect between academic AI research in orthognathic surgery and commercially available virtual surgical planning software as a critical translational challenge: the vast majority of AI prediction models developed in research settings have not been integrated into the commercially deployed VSP platforms that clinicians actually use in daily practice, meaning that their demonstrated technical advantages remain inaccessible to the clinicians who could benefit from them. Bridging this translational gap requires not only continued technical development and clinical validation, but also deliberate engagement between academic research groups and commercial software developers, and the establishment of regulatory frameworks specifically designed for AI-based surgical planning tools that currently exist in a legal and approval grey zone in most jurisdictions.

The consistently identified methodological limitations across the primary AI orthognathic surgery prediction literature — particularly the small sample sizes and single-centre derivation and validation of most published models — reflect a structural challenge specific to this field: the paired preoperative and postoperative high-quality imaging datasets required to train and validate AI prediction models are expensive to acquire, require substantial clinical infrastructure, and are available at scale only at specialist orthognathic surgery centres with established research programs. International data-sharing initiatives, similar to those that have accelerated AI development in other medical imaging domains, could substantially increase the size and diversity of available training datasets, enabling the development of more robust and generalizable prediction models than any single centre could produce independently.

Several important limitations characterize the body of evidence synthesized in this review. First, the primary AI prediction studies included through the systematic and scoping reviews generally evaluated model performance in retrospective or cross-validation settings using data from the same clinical centre as the training cohort, without prospective evaluation in patients undergoing live surgical planning — the clinical context in which prediction accuracy ultimately determines patient outcome and surgical decision-making quality. Second, the AI prediction models reviewed here were evaluated predominantly on standard orthognathic surgery cases from academic referral centres, without specific assessment of model performance in clinically challenging cases involving prior craniofacial surgery, asymmetry correction, or distraction osteogenesis, where conventional prediction is most unreliable and the need for AI most acute. Third, no included study reported patient-reported outcome data comparing AI-predicted versus actual postoperative facial appearance from the patient's own perspective — an outcome dimension of fundamental importance for evaluating whether AI prediction tools actually improve the experience and satisfaction of patients undergoing orthognathic surgery.

Future research priorities for AI-based orthognathic surgery prediction should include: large-scale, multicentre prospective validation studies enrolling patients across multiple specialist centres, ethnicities, and craniofacial phenotypes, with AI-generated predictions evaluated against actual postoperative outcomes using standardized, pre-specified accuracy metrics; direct randomized comparison of AI-guided versus conventional surgical planning on patient-reported aesthetic satisfaction, functional outcomes, and surgical revision rates; accelerated integration of validated AI prediction models into commercially available virtual surgical planning software platforms, with clinician usability testing and iterative refinement; development of regulatory frameworks specifically addressing AI-based surgical planning tools, enabling market approval based on prospective clinical performance data; and patient-facing AI prediction interfaces that communicate predicted facial changes in terms directly meaningful to patients — including photo-realistic visualizations of predicted postoperative appearance — to support truly informed consent and patient-centred surgical decision-making.

Conclusion

This systematic review establishes that AI-based models for predicting skeletal and soft tissue changes following orthognathic surgery demonstrate consistently superior prediction accuracy, speed, and clinical usability compared with conventional cephalometric ratio-based and biomechanical finite element simulation methods, with joint face-skeletal architectures simultaneously predicting bone repositioning and soft tissue response representing the current technical state of the art. Foundational enabling technologies — including deep learning-based automatic craniofacial segmentation and deep learning surrogates for finite element biomechanical simulation — have addressed critical computational bottlenecks that previously prevented AI-based prediction from operating at the speed required for interactive virtual surgical planning workflows. Innovative primary model development studies applying graph neural networks combined with diffusion model architectures, and the first large-scale AI-based evaluation of aesthetic outcomes following orthognathic surgery, further extend the clinical scope of AI in this field beyond anatomical prediction alone. Despite this substantial technical progress, the field faces a well-defined and urgent translational challenge: the absence of large-scale multicentre prospective clinical validation, the limited integration of research AI models into commercially deployed virtual surgical planning software, and the lack of patient-reported outcome data linking AI prediction quality to patient satisfaction and surgical outcome represent the critical barriers that must be overcome before AI-based orthognathic surgery prediction can fulfil its substantial clinical promise in routine oral and maxillofacial surgery practice.

References

Almarhoumi, A. A. (2024). Accuracy of artificial intelligence in predicting facial changes post-orthognathic surgery: A comprehensive scoping review. Journal of Clinical and Experimental Dentistry, 16(5), e624–e633. https://doi.org/10.4317/jced.61500

Cheng, M., Zhang, X., Wang, J., Yang, Y., Li, M., Zhao, H., Xiao, Y., Zhang, Y., & Zhang, X. (2023). Prediction of orthognathic surgery plan from 3D cephalometric analysis via deep learning. BMC Oral Health, 23(1), 161. https://doi.org/10.1186/s1154-171-02844-z

Dot, G., Schouman, T., Chang, S., Rafflenbeul, F., Kerbrat, A., Rouch, P., & Gajny, L. (2022). Fully automatic segmentation of craniofacial soft tissues in MRI before orthognathic surgery using deep learning. Investigative Radiology, 57(3), 208–216. https://doi.org/10.1097/RLI.0000000000000831

Kim, I. H., Jeong, J., Kim, J. S., Lim, J., Cho, J. H., & Hong, M. (2025). Predicting orthognathic surgery results as postoperative lateral cephalograms using graph neural networks and diffusion models. Nature Communications, 16(1), 2586. https://doi.org/10.1038/s4154-171-57669-x

Lampen, N., Kim, D., Fang, X., Xu, X., Kuang, T., Deng, H. H., Barber, J. C., Gateno, J., Xia, J., & Yan, P. (2022). Deep learning for biomechanical modeling of facial tissue deformation in orthognathic surgical planning. International Journal of Computer Assisted Radiology and Surgery, 17(5), 945–952. https://doi.org/10.1007/s1154-171-0154-171

Liebregts, J., Xi, T., Timmermans, M., de Koning, M., Bergé, S., Hoppenreijs, T., & Maal, T. (2015). Accuracy of three-dimensional soft tissue simulation in bimaxillary osteotomies. Journal of Cranio-Maxillo-Facial Surgery, 43(3), 329–335. https://doi.org/10.1016/j.jcms.2014.12.010

Mohaideen, K., Negi, A., Verma, D. K., Kumar, N., Sennimalai, K., & Negi, A. (2022). Applications of artificial intelligence and machine learning in orthognathic surgery: A scoping review. Journal of Stomatology, Oral and Maxillofacial Surgery, 123(6), e962–e972. https://doi.org/10.1016/j.jormas.2022.06.027

Motamedian, S. R., Mohaghegh, S., Niazmand, M., Mohammad-Rahimi, H., Ahmadi, N., Yaseri, M., & Haeri Boroojeni, H. S. (2025). Application of artificial intelligence in orthognathic surgery: A scoping review. BioMed Research International, 2025, 8284581. https://doi.org/10.1155/bmri/8284581

Patcas, R., Bernini, D. A. J., Volokitin, A., Agustsson, E., Rothe, R., & Timofte, R. (2019). Applying artificial intelligence to assess the impact of orthognathic treatment on facial attractiveness and estimated age. International Journal of Oral and Maxillofacial Surgery, 48(1), 77–83. https://doi.org/10.1016/j.ijom.2018.07.010

Salazar, D., Rossouw, P. E., Javed, F., & Michelogiannakis, D. (2024). Artificial intelligence for treatment planning and soft tissue outcome prediction of orthognathic treatment: A systematic review. Journal of Orthodontics, 51(2), 107–119. https://doi.org/10.1177/14653125231203743

Takeshita, W. M., Silva, T. P., Trindade de Souza, L. L., & Tenorio, J. M. (2024). State of the art and prospects for artificial intelligence in orthognathic surgery: A systematic review with meta-analysis. Seminars in Orthodontics, 30, 185–195. https://doi.org/10.1016/j.sodo.2024.01.009

Wang, T., Chen, H., Song, G., & Han, B. (2025). Traditional and artificial intelligent methods in predicting maxillofacial soft tissue morphology after orthognathic surgery: A narrative review. International Journal of Dentistry, 2025, 6268492. https://doi.org/10.1155/ijod/6268492

Wang, X., Chen, J., Zheng, Q., Kang, T., Hu, G., Zhou, M., Wang, H., Zhang, W., & Chen, X. (2025). Artificial intelligence in joint face–skeletal prediction for orthognathic procedures: A systematic review. Journal of Cranio-Maxillo-Facial Surgery. https://doi.org/10.1016/j.jcms.2025.003300