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Review Article

Artificial Intelligence and the Digital Workflow in Facial Bone Surgery: A Narrative Review of Current Evidence and Future Directions

Abdulmajeed A. Aljabr

Department of Preventive Dental Sciences, College of Dentistry, Majmaah University, Al Majmaah, 11952, Saudi Arabia

ORCID: 0009-0002-8281-5539

***Corresponding author**

Abdulmajeed A. Aljabr, Department of Preventive Dental Sciences, College of Dentistry, Majmaah University, Al Majmaah, 11952, Saudi Arabia, Email: A.Jabr@mu.edu.sa

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Abstract

Background: The surgical management of the facial skeleton has been reshaped over the past two decades by a sequence of digital technologies that now extend across the entire care pathway, from image acquisition and diagnosis to planning, intraoperative execution, and follow-up. Artificial intelligence (AI) has entered this landscape more recently, and its precise contribution to facial bone surgery, as distinct from the broader fields of craniomaxillofacial and aesthetic surgery, remains incompletely defined.

Methods: We performed a narrative review of the English-language literature, prioritizing studies published in peer-reviewed journals indexed in major databases, that examined the application of AI and allied digital technologies, including automated segmentation, virtual surgical planning, computer-aided design and additive manufacturing, intraoperative navigation and augmented reality, and piezoelectric osteotomy, to facial bone surgery.

Results: Automated deep-learning segmentation of craniofacial computed tomography now approaches or exceeds the accuracy of manual tracing while reducing processing time by an order of magnitude. Virtual surgical planning has become the standard of care in orthognathic and reconstructive procedures, with systematic evidence of accuracy equal to or better than conventional model surgery. Machine-learning models predict postoperative facial soft-tissue change and, in early studies, propose surgical plans directly from cephalometric data. Patient-specific implants fabricated by additive manufacturing have demonstrated high success rates, with pooled success approaching 95%, particularly in orbital and mandibular reconstruction. Intraoperative navigation and augmented reality improve precision in anatomically complex regions, and piezoelectric osteotomy reduces collateral soft-tissue injury.

Conclusions: AI and digital technologies have moved from adjuncts to integral components of facial bone surgery. They improve precision, efficiency, and reproducibility, yet high-level comparative evidence remains limited, and questions of generalizability, regulation, and cost persist. Progress depends on prospective multicenter validation and on the development of interoperable, transparent, and clinically integrated systems.

INTRODUCTION

Facial bone surgery encompasses the surgical management of the osseous framework of the face, including the mandible, maxilla, zygomaticomaxillary complex, orbits, and the frontal and nasal skeleton. Its clinical territory includes the acute reconstruction of facial trauma, the correction of congenital and developmental craniofacial deformities, ablative and reconstructive surgery for tumors, and orthognathic surgery for dentofacial disproportion. The discipline is defined by a distinctive tension: the facial skeleton must satisfy demanding functional requirements, including occlusion, mastication and deglutition, airway patency, globe position and binocular vision, and the protection of neurovascular structures, while simultaneously restoring a region whose appearance carries profound psychological and social weight. For most of its history, this reconciliation depended on the surgeon's accumulated judgment, planar radiographs, and a degree of intraoperative improvisation that the modern era increasingly regards as unacceptable.

The past two decades have produced a fundamental reorganization of this workflow. The introduction of cone-beam computed tomography (CBCT) and high-resolution multidetector CT made three-dimensional (3D) representation of the facial skeleton routine. Virtual surgical planning (VSP) followed, allowing osteotomies,

segment repositioning, and intermediate splint design to be rehearsed on a computer rather than on plaster models. Computer-aided design (CAD) and additive manufacturing extended this capability into the operating room through patient-specific surgical guides and, subsequently, patient-specific implants (PSIs). More recently, artificial intelligence, and deep learning in particular, has begun to automate the labor-intensive steps that remained, including image segmentation, cephalometric analysis, soft-tissue outcome prediction, and even the generation of surgical plans.

The purpose of this narrative review is to examine the current and emerging role of AI and allied digital technologies specifically within facial bone surgery. Previous reviews have addressed AI in plastic and aesthetic surgery [1,2], or in orthognathic surgery in isolation [3,4]. Our aim is to consider the digital workflow as a continuum, from imaging and segmentation, through planning and prediction, to intraoperative execution and implant fabrication, and to appraise critically the evidence supporting each stage. We also consider the limitations that currently constrain clinical translation and the directions in which the field is likely to move. The review is intended for clinicians who wish to understand what these technologies can and cannot yet do, and for investigators planning the next generation of studies in this rapidly evolving field.

THE DIGITAL FOUNDATION: IMAGING AND AUTOMATED SEGMENTATION

From Two-Dimensional to Three-Dimensional Imaging

The digital workflow begins with volumetric imaging. Multidetector CT and, increasingly, CBCT provide isotropic or near-isotropic datasets from which the facial skeleton can be reconstructed in three dimensions. Segmentation, the process of assigning each voxel to an anatomical structure, is the essential first step: every downstream application, including VSP, implant design, and surgical navigation, depends on an accurate representation of the bone surface. Manual segmentation, performed slice by slice with thresholding and region-growing tools, is accurate but slow, and its quality varies with operator experience. For many years this labor cost was a practical barrier to the routine use of the digital workflow, particularly in centers without dedicated engineering support.

Deep Learning for Automated Segmentation

Deep convolutional networks, and in particular encoder-decoder architectures of the U-Net family, have changed this calculation. Trained on large sets of manually annotated scans, these models segment the mandible, maxilla, and craniofacial complex with accuracy that consistently approaches, and in some studies exceeds, that of manual tracing, while reducing processing time by orders of magnitude. A systematic review of AI-based automated segmentation in dentomaxillofacial imaging concluded that automatic techniques were consistently faster than manual segmentation and more than 90% accurate [5]. Deep-learning models have been reported for the fully automatic segmentation of the maxillary sinus [6], the mandible and periodontal structures [8], the mandibular canal [7], and individual teeth [9], and similar approaches now underpin commercial planning platforms.

Clinical Implications

Automated segmentation matters because it removes the rate-limiting step of the digital workflow. When segmentation is fast, reproducible, and independent of operator skill, VSP and PSI fabrication become practical for routine cases rather than reserved for complex reconstructions. The caveat is that published models are frequently trained and tested on single-institution datasets, and their performance on unusual anatomy, metallic artifact, or pediatric craniofacial morphology is less well established. Clinicians should therefore regard automated segmentation as a high-quality starting point that still requires visual verification before it is used for planning or fabrication [5-7].

VIRTUAL SURGICAL PLANNING AND ITS EVOLUTION

From Model Surgery to the Virtual Environment

VSP replaces traditional model surgery with a computer-based simulation. The segmented 3D model is subjected to cephalometric analysis, osteotomy lines are defined, and the bony segments are repositioned according to the surgical objectives. The resulting plan is transferred to the operating room through patient-specific cutting guides and occlusal splints manufactured by additive manufacturing. The advantages are well recognized: the plan is visible to the entire team before surgery, the surgeon can test alternative movements, and the guides reduce intraoperative judgment calls [10,11]. In-house workflows, in which the entire process is performed within the treating department, have been shown to be feasible and accurate in retrospective series [12].

Evidence for Accuracy

The accuracy of VSP has been examined in several

systematic reviews. An early systematic review concluded that virtual planning is an accurate and reproducible method for orthognathic treatment planning, while calling for additional clinical trials [13]. A subsequent systematic review and meta-analysis comparing virtual and traditional surgical planning found that VSP significantly reduced bimaxillary osteotomy planning time, with accuracy at least comparable to conventional methods [14]. More recent comparative studies have confirmed that three-dimensional VSP achieves clinically acceptable accuracy when measured against the planned and achieved positions of the maxilla and mandible [15,16]. These findings have made VSP the default approach in many centers for orthognathic, temporomandibular joint, and reconstructive procedures [10,11].

Limitations

The principal weakness of VSP is not the bone but the soft tissue. Prediction of the postoperative facial appearance remains approximate, because current algorithms model soft-tissue change with simplified biomechanical assumptions. This limitation is directly relevant to patients whose primary motivation for orthognathic surgery is aesthetic, and it is the gap that AI-based prediction methods, discussed below, are beginning to address. Additional limitations include the cost of commercial planning services, the learning curve for surgeons and engineers, and the transfer error inherent in translating a virtual plan to the operating room [13,14].

ARTIFICIAL INTELLIGENCE IN PLANNING AND OUTCOME PREDICTION

Automated Cephalometric Analysis

Cephalometric analysis, the quantification of skeletal and dental relationships, is a repetitive and time-consuming task that is well suited to automation. Deep-learning landmark detection now identifies cephalometric points with accuracy comparable to experienced observers, and automated analysis is integrated into several commercial planning platforms. The practical benefit is twofold: it reduces the time required for planning, and it removes inter-observer variability from the diagnostic phase [3,4,17].

AI-Assisted Generation of Surgical Plans

A more ambitious application is the direct generation of surgical plans. Using deep learning trained on large datasets of completed orthognathic cases, investigators have proposed models that predict the surgical plan from three-dimensional cephalometric analysis, effectively learning the relationship between presenting deformity and the osteotomy movements performed by expert surgeons [18]. Related work has explored joint prediction of skeletal and facial changes, with the aim of producing plans that optimize both functional and aesthetic outcomes [19]. These models are promising but remain experimental: they are trained on the practice of particular centers, and their recommendations must still be reviewed and adjusted by the surgeon [18,19].

Soft-Tissue Outcome Prediction

Prediction of the postoperative facial appearance is the area in which AI has made the most visible progress. A landmark study demonstrated that deep-learning systems can predict the three-dimensional facial topography after orthognathic surgery and orthodontic treatment with clinically useful accuracy [20]. Geometric deep learning has been used to simulate postoperative facial appearance directly on the facial mesh, enabling rapid exploration of alternative plans [21], and deep-learning models trained on finite-element simulations have been shown to approximate biomechanical soft-tissue deformation at a fraction of the computational cost [22]. Two recent scoping reviews have synthesized this literature, concluding that AI demonstrates significant potential for improving the precision of facial outcome prediction after orthognathic surgery, while noting heterogeneity in study design and reporting [3,4].

The Broader AI Landscape in Facial Surgery

These developments sit within a wider movement. A large review of AI in plastic and reconstructive surgery emphasized the potential of machine learning to enhance surgical precision and improve outcome prediction across the specialty [1], and a review of facial aesthetic surgery identified 66 studies using AI or machine learning up to early 2024, spanning diagnosis, planning, and outcome assessment [2]. Reviews focused on pediatric craniofacial surgery have similarly highlighted the diagnostic and planning applications of AI in conditions such as craniosynostosis [23], and narrative overviews of the field have described the broader trajectory toward data-driven, predictive oral and maxillofacial surgery [17]. The facial bone surgery-specific literature is smaller but growing, and it is the focus of this review.

PATIENT-SPECIFIC IMPLANTS AND ADDITIVE MANUFACTURING

Principles and Materials

Patient-specific implants are fabricated from the patient's own imaging data through a CAD and additive

manufacturing workflow. Titanium alloys, processed by selective laser melting, remain the most widely used material, and polyether ether ketone (PEEK) has gained acceptance for craniofacial applications where radiolucency and low thermal conductivity are advantageous [24,25]. Porous lattice designs, which promote osseointegration while reducing stiffness, are an active area of development. The same workflow produces the cutting guides and splints used to execute the virtual plan, so that planning, guides, and implants form a single integrated system [26,27].

Evidence of Clinical Outcomes

A systematic review and meta-analysis of 3D-printed patient-specific implants in maxillofacial reconstruction reported a pooled implant success rate of 94.7%, with reduced operating time and improved anatomical restoration compared with conventional approaches [28]. Scoping reviews of PSI customization and fabrication methods have confirmed the breadth of clinical applications and the consistency of reported benefits, while emphasizing the heterogeneity of outcome measures across studies [29,30]. Surveys of surgeons suggest that patient-specific mandibular and orbital implants are widely perceived as superior to conventional plates [30], and narrative reviews have documented the advantages of PSIs in terms of surgical accuracy, reduced operative time, and shorter recovery [31,32].

Orbital Reconstruction as a Paradigm

The orbit is the clearest demonstration of the value of PSIs, because its anatomy is unforgiving and its reconstruction is judged by objective measures of volume and globe position. A systematic review and meta-analysis of orbital reconstruction found that patient-specific implants achieved more accurate restoration of orbital volume than conventional techniques [33]. Comparative studies have reported superior orbital volume restoration and globe positioning, with reduced complication and revision rates, for PSIs in post-traumatic reconstruction [34], and randomized evidence has shown that pre-shaped implants produced on patient-specific 3D models fit more accurately than manually contoured implants [35]. The evidence is not entirely one-sided: one comparative study found that PSIs improved orbital volume accuracy without reducing the overall complication rate relative to preformed implants [36], and pre-bent hybrid titanium meshes have been shown to reduce operating time while achieving equally accurate volume restoration [37]. Taken together, the literature supports the use of patient-specific implants for large, complex, or secondary orbital defects, where the margin for error is smallest [33-38].

Economic and Workflow Considerations

The principal barriers to wider adoption of PSIs are cost and lead time. Commercial fabrication adds expense, and the interval between imaging and implant delivery is incompatible with urgent trauma surgery. In-house fabrication reduces both cost and delay and has become the preferred model in many academic centers, although it requires investment in hardware, software, and trained personnel [12,29]. The reduction in operating time associated with PSIs partially offsets their upfront cost, and this trade-off is likely to improve as additive manufacturing technology matures [28,37].

INTRAOPERATIVE TECHNOLOGY: NAVIGATION, AUGMENTED REALITY, AND PIEZOSURGERY

Intraoperative Navigation

Intraoperative navigation, using optical or electromagnetic tracking of surgical instruments relative to the preoperative image, increases the precision and safety of surgery in anatomically complex regions such as the orbit, skull base, and temporomandibular joint [39]. Navigation is particularly valuable where normal anatomical landmarks have been destroyed by trauma or tumor, and where the target of surgery is defined by the virtual plan rather than by visible anatomy [39,40] (Table 1).

Augmented and Mixed Reality

Augmented reality (AR) projects the virtual plan onto the surgical field, either through head-mounted displays or through overlay on the operating microscope or monitor. Preliminary clinical studies report millimeter-level accuracy for AR-guided craniofacial procedures and improved intraoperative orientation [41], and dedicated AR navigation platforms have been developed and applied across craniomaxillofacial and head and neck surgery [42]. The technology remains at an early stage, with issues of registration stability, ergonomics, and occlusion of the surgical field still to be resolved, but its trajectory is clear [41,42].

Table 1: Summary of the digital workflow in facial bone surgery

Workflow stage	Technology	Reported benefit	Key evidence
Imaging / segmentation	AI automated segmentation	>90% accuracy; faster	Park [5]; Choi [6]
Planning	Virtual surgical planning	Less planning time; accurate	Alkhayer [13]; Alkaabi [14]
Outcome prediction	Deep-learning soft-tissue prediction	Predicts facial appearance	Tanikawa [20]; Ma [21]
Implant fabrication	3D-printed PSIs (titanium, PEEK)	94.7% success; accurate orbit	Yousif [28]; Kotecha [33]
Intraoperative	Navigation, AR, piezosurgery	Precision; fewer complications	Kang [39]; Pagotto [47]

Piezoelectric Osteotomy

Piezoelectric surgery uses modulated ultrasonic vibration to cut mineralized tissue selectively while sparing soft tissue, and it has become an established tool in facial bone surgery [43]. A systematic review and meta-analysis found that piezosurgery reduced complications associated with orthognathic surgery, including bleeding and nerve injury, relative to conventional osteotomy [44,47], and experimental studies have confirmed more favorable bone-healing responses compared with rotary instruments [46]. Although not itself an AI technology, piezosurgery is part of the broader trend toward precise, minimally injurious bone surgery, and it complements the planning and navigation technologies discussed above [43,44].

CHALLENGES AND LIMITATIONS

The enthusiasm surrounding these technologies should be tempered by an honest appraisal of the evidence. First, the quality of the literature is uneven. Much of the evidence on VSP, PSIs, and AI prediction derives from retrospective, single-center series, and randomized or prospective comparative studies remain scarce [13,28]. Second, the generalizability of AI models is a genuine concern: models trained on the imaging and practice of one center may not perform as well on the diverse anatomy, imaging protocols, and clinical conventions encountered elsewhere [3,4]. External validation, preferably on multicenter data, is the exception rather than the rule. Third, regulatory and medicolegal frameworks for AI-assisted surgical decision-making are still evolving, and the question of who is responsible when a model's recommendation is followed and the outcome is poor remains unresolved. Fourth, cost and access divide the field: the full digital workflow is available in well-resourced centers but remains out of reach in many settings, and this disparity has implications for equity of care. Finally, there are professional concerns. Reliance on automated planning and prediction carries a risk of deskilling, and the opacity of deep-learning models can undermine the surgeon's ability to explain decisions to patients. These considerations argue for transparency, clinician oversight, and the development of explainable models as preconditions for responsible adoption [1,4,7].

FUTURE DIRECTIONS

Several developments are likely to shape the next phase of this field. Foundation models and multimodal AI, trained on imaging, clinical, and outcome data simultaneously, may eventually support end-to-end planning that integrates skeletal, dental, and soft-tissue considerations in a single model. Federated learning offers a route to larger, more diverse training datasets without centralizing identifiable patient data, addressing both generalizability and privacy. Digital twins, in which a living computational model of the patient is updated with intraoperative and postoperative data, could enable personalized prediction of healing and long-term stability. In the operating room, the combination of navigation, augmented reality, and robotic assistance is converging toward semi-autonomous execution of the virtual plan. Materials science is contributing biodegradable and sensor-equipped implants that could monitor healing and signal complications. Realizing these possibilities will require prospective multicenter trials, standardized outcome reporting, and reporting guidelines specific to AI in surgery [1-17].

CONCLUSION

Facial bone surgery has entered a genuinely digital era. Automated segmentation, virtual surgical planning, patient-specific implants, intraoperative navigation, and artificial intelligence now form a coherent workflow that improves precision, efficiency, and reproducibility across the discipline. The evidence for each component is substantial but uneven, and the strongest data currently support virtual planning and patient-specific reconstruction of the orbit and mandible. Artificial intelligence is the most rapidly evolving component of this workflow, and its contributions to segmentation, planning, and outcome prediction are already clinically useful, but they remain adjuncts to, rather than replacements for, surgical judgment. The responsibility of the specialty is to ensure that these technologies are adopted on the basis of evidence, validated on diverse populations, and integrated in ways that preserve the surgeon's role as the accountable decision-maker. If that discipline is maintained, the digital workflow will continue to raise the standard of care for patients undergoing facial bone surgery.

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