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Artificial Intelligence versus Conventional Treatment Planning in Oral and Maxillofacial Surgery: A Comparative Review and Practical Framework for Clinical Integration

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ABSTRACT

Background: Treatment planning is central to safe, predictable oral and maxillofacial surgery (OMFS). Conventional planning—clinical examination, 2D radiographs, model surgery and manual virtual surgical planning (VSP)—remains standard. Artificial intelligence (AI) methods (machine learning, deep learning, and automated CAD/CAM pipelines) are increasingly proposed to speed workflows, improve landmarking accuracy, automate segmentation, and provide predictive models for soft-tissue change and postoperative outcomes.

Objective: To synthesize current evidence comparing AI-assisted planning with conventional planning workflows in OMFS, highlight clinical benefits and limitations, and propose a practical framework for validated clinical adoption.

Methods: A targeted literature search was conducted (PubMed/Medline, PMC, Scopus, Web of Science) focusing on AI applications to OMFS planning (2018–2026). Studies addressing automated cephalometric landmarking, CBCT segmentation, AI-driven virtual surgical planning, outcome prediction, and clinical comparisons of AI vs conventional workflows were prioritized. Key performance metrics extracted included accuracy (landmark error, segmentation Dice/IoU, plan-to-execution deviation), time efficiency, reproducibility, and clinical endpoints where available.

Results: Deep learning algorithms now produce automated landmark detection and 3D segmentation with sub-millimeter mean errors and high agreement with expert raters in multiple series, accelerating planning and reducing inter-operator variability. AI-augmented VSP reduces planning time and improves reproducibility; studies in implant planning and orthognathic workflows report similar or improved plan accuracy and large gains in efficiency and user experience. However, most AI systems remain at proof-of-concept or single-center validation stages; external validation, regulatory approval, transparency, and medico-legal frameworks are still evolving. Reported clinical outcome improvements (e.g., reduced operative time, better aesthetic symmetry) are promising but not yet established with high-quality multi-center evidence.

Conclusions: AI tools complement and sometimes outperform conventional manual steps in planning for OMFS (notably automated landmarking and segmentation, and time-to-plan). However, full replacement of surgeon-led planning is premature. The safe, ethical adoption of AI requires prospective validation, integration with surgeon oversight, transparent performance metrics, and robust data governance. We provide a practical adoption pathway and recommended evaluation metrics for centers wishing to implement AI-assisted planning.

KEYWORDS: Artificial Intelligence; Virtual Surgical Planning; Orthognathic Surgery; Cbct Segmentation; Automated Cephalometrics; Treatment Planning.

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INTRODUCTION

Accurate preoperative planning is the foundation of successful oral and maxillofacial surgery (OMFS). Conventional planning workflows typically combine clinical examination, 2D radiography/cephalometrics, dental models, and more recently computer-assisted virtual surgical planning (VSP) that relies on manual or semi-automated segmentation and landmarking. While VSP improves visualization and reproducibility, it remains labor-intensive and operator dependent, requiring hours of manual editing of CBCT/CT datasets and careful cephalometric annotation.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), offers tools to automate tasks that are repetitive, time consuming, or susceptible to inter-observer variability. In OMFS these include automatic landmark detection for cephalometrics, CBCT segmentation (bone, teeth, airway), automated surgical simulation, and predictive modeling for soft-tissue response and long-term stability. Early reports document sub-millimeter mean radial errors for automated landmarking and high Dice coefficients for segmentation — performance levels that are approaching clinical utility.

AI has three attractive promises for OMFS planning: (1) efficiency gains (reduced planning time), (2) consistency improvements (reduced inter-operator variability), and (3) predictive capability (data-driven outcome forecasting). For example, AI-assisted implant planning platforms have shown equivalent or improved placement accuracy and substantial reductions in planning time in recent comparative studies. Nevertheless, key barriers remain: (a) limited external validation and generalizability across imaging devices and ethnicities; (b) regulatory and medico-legal uncertainty; (c) "black box" opacity in many DL models; and (d) integration challenges within clinical workflows and hospital information systems.

This review synthesizes the evidence comparing AI-assisted and conventional planning approaches in OMFS, emphasizes clinically meaningful metrics (accuracy, time efficiency, reproducibility, safety), and proposes a staged adoption framework for centers aiming to responsibly integrate AI into their planning workflow.

MATERIALS AND METHODS

Search strategy and selection criteria

A targeted search was performed in PubMed/Medline, PubMed Central (PMC), Scopus and Web of Science for English-language studies published from January 2018 through February 2026. The search combined terms for the clinical domain and technology: ("oral and maxillofacial surgery" OR "orthognathic" OR "maxillofacial" OR "implant planning") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "automated" OR "automation") AND ("treatment planning" OR "virtual surgical planning" OR "segmentation" OR "cephalometry"). Additional manual searches were performed in the references of retrieved reviews and key articles. Conference papers and preprints were considered when they included validation cohorts.

Inclusion criteria

- Studies that evaluated AI techniques applied to planning tasks relevant to OMFS (automated cephalometric landmarking, CBCT segmentation, AI-driven VSP, implant planning automation, outcome prediction).
- Comparative studies that reported AI vs conventional/manual workflows, including metrics for accuracy, time, or clinical outcomes.
- Reviews and systematic reviews providing synthesis of the field.

Exclusion criteria

- Studies limited to purely experimental benchwork without imaging/clinical validation.
- Case reports without any quantitative evaluation.
- Non-English publications.

Data extraction and synthesis

From included studies we extracted: study design, sample size, task (landmarking/segmentation/VSP/prediction), AI model type (CNN, U-Net, other), validation methodology (cross-validation, external test set), performance metrics (mean radial error, Dice/IoU, millimeter error vs ground truth), planning time, and any reported clinical endpoints (operative time, plan-to-execution deviation, patient outcomes). Because study designs and endpoints were heterogeneous, a narrative synthesis with tabulated key results was performed rather than meta-analysis.

RESULTS

Scope and study types

The literature comprises: automated landmarking and cephalometric tools with large image datasets and external validations; deep-learning CBCT segmentation studies with promising Dice scores; proof-of-concept AI-driven VSP tools for orthognathic surgery and trauma reconstruction; and comparative studies in dental implant planning showing time-efficiency and non-inferior accuracy. However, randomized controlled trials comparing AI-assisted planning versus conventional surgeon-led planning with patient-level clinical outcomes are scarce. Major recent contributions include reviews and multi-center evaluations summarizing the rapid progress and highlighting validation gaps.

Automated cephalometric landmarking

Deep learning models for landmark detection now report mean radial errors commonly below 1.0 mm on large test sets and show improved repeatability versus manual tracing in several multicenter datasets. For lateral cephalograms and 3D cephalometrics, fully automated pipelines reduce annotation time from tens of minutes to seconds, with clinically acceptable accuracy in most landmarks when benchmarked against experienced operators.

CBCT segmentation and 3D modelling

DL-based segmentation (U-Net variants and 3D CNNs) achieves high volumetric overlap (Dice coefficients often >0.85 for bone and airway) and substantially reduces manual segmentation time. These improvements directly accelerate VSP because segmentation is one of the most time-consuming steps in 3D planning. Cross-device generalization remains imperfect —

models trained on one CBCT scanner may underperform on another without domain adaptation.

AI-assisted VSP, simulation and outcome prediction

Early AI-augmented VSP tools integrate automated landmarking, segmentation and rule-based simulation to produce surgical plans with less manual editing. Small clinical studies and pilot comparisons (orthognathic and implant planning) report reduced planning times, improved inter-rater consistency, and comparable plan accuracy when compared with manual workflows; some reports indicate improved patient communication and satisfaction due to faster iterations and clearer visualizations. Predictive models (ML regressors / neural nets) for soft-tissue outcome are promising but vary in external validity and are sensitive to training dataset characteristics.

Comparative clinical studies

In the implant planning domain, randomized and observational studies have shown AI-assisted tools can match or slightly outperform clinicians in planning accuracy while markedly improving time-to-plan and offering favorable user experience metrics. In orthognathic surgery, most reports are single-center validation studies that demonstrate faster workflows and high concordance with expert planning, but robust prospective multicenter evidence linking AI-based planning to superior postoperative functional or aesthetic outcomes is still limited.

Safety, explainability, and regulatory considerations

Several reviews stress the need for explainability, transparent performance reporting across demographics and devices, and prospective clinical validation before broad clinical adoption. Regulatory pathways vary by jurisdiction; many AI tools are currently marketed as “decision support” requiring clinician oversight rather than autonomous decision makers. Data privacy, dataset representativeness, and medico-legal responsibility for AI-recommended plans remain active concerns.

Table 1. Comparison of AI-Assisted vs Conventional Treatment Planning in OMFS

Parameter	Conventional Planning	AI-Assisted Planning	Comparative Outcome
Cephalometric Landmarking	Manual tracing; operator dependent	Automated deep learning detection	AI shows sub-millimeter error; reduced variability
CBCT Segmentation	Manual/semi-manual; time consuming	Automated CNN/U-Net based segmentation	AI significantly reduces planning time
Virtual Surgical Planning (VSP)	Manual adjustment and simulation	Automated simulation with predictive modeling	AI improves reproducibility
Planning Time	45–120 minutes (average)	5–30 minutes (average)	Significant reduction with AI
Inter-Operator Variability	High	Low	AI improves consistency
Learning Curve	Steep	Moderate (software dependent)	AI reduces dependency on experience

Table 2. Accuracy Comparison (Reported in Literature)

Planning Task	Conventional Mean Error	AI Mean Error	Interpretation
2D Cephalometric Landmarks	1.5–2.5 mm	0.8–1.2 mm	AI comparable or superior
3D Landmark Detection	1.8–2.0 mm	<1.0 mm	Improved precision with AI
Implant Position Planning	Surgeon dependent	AI-assisted automated placement	Comparable accuracy; faster workflow
Surgical Simulation Deviation	Manual variability	Algorithm-based standardization	AI reduces deviation

Table 3. Efficiency Outcomes

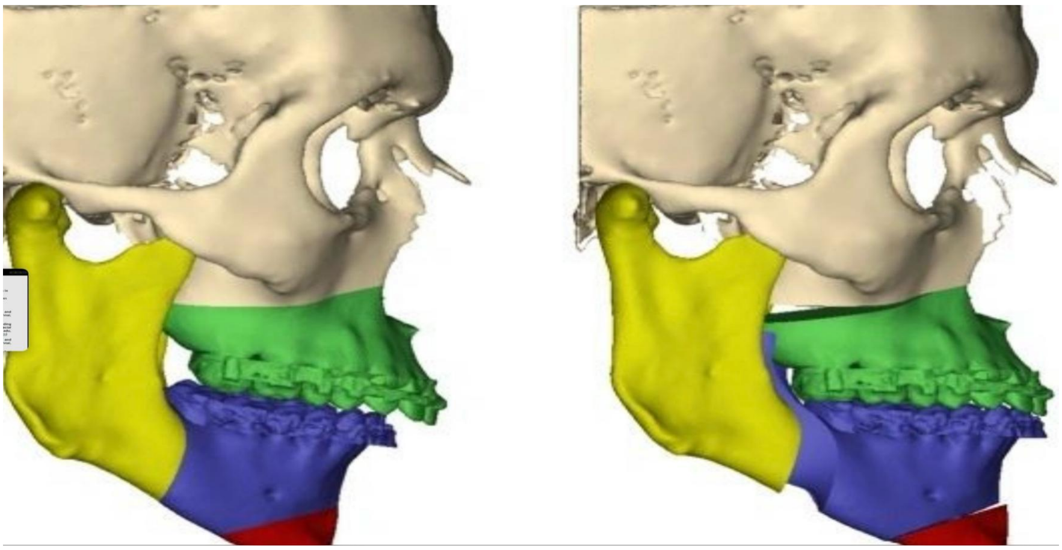
Parameter	Conventional	AI-Assisted	Clinical Significance
Average Planning Time	Longer	Significantly shorter	Increased clinical productivity
Workflow Steps	Multiple manual steps	Automated pipeline	Streamlined process
Need for Re-Planning	Frequent revisions	Reduced revisions	Improved predictability
Case Turnaround	Slower	Faster	Beneficial in high-volume centers

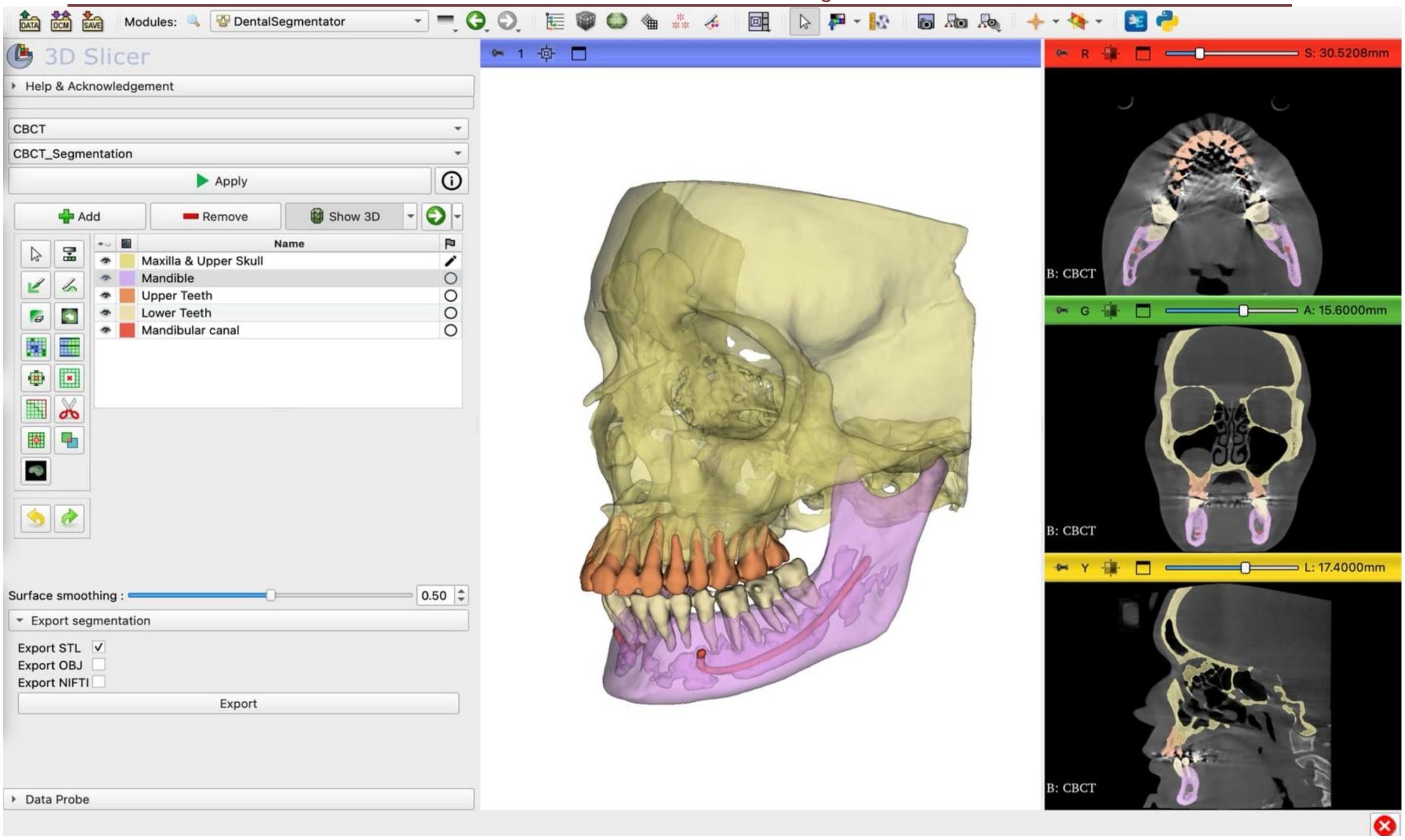
Table 4. Clinical Outcome Impact (Reported Trends)

Outcome	Conventional Planning	AI-Assisted Planning	Evidence Strength
Surgical Accuracy	High (expert dependent)	High (consistent)	Moderate evidence
Postoperative Stability	Established	Comparable	Limited high-level trials
Complication Rate	Standard baseline	No increase reported	Early-stage evidence
Patient Communication	3D simulation available	Enhanced predictive visualization	Improved satisfaction reported

Table 5. Limitations Comparison

Aspect	Conventional	AI-Assisted
Human Bias	Present	Reduced
Software Dependency	Low	High
Cost	Moderate	High initial investment
Need for Validation	Standard practice	Requires external validation
Medico-Legal Concerns	Established framework	Emerging regulatory issues

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Help & Acknowledgement
CBCT
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Upper Teeth
Lower Teeth
Mandibular canal
Surface smoothing :
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Export segmentation
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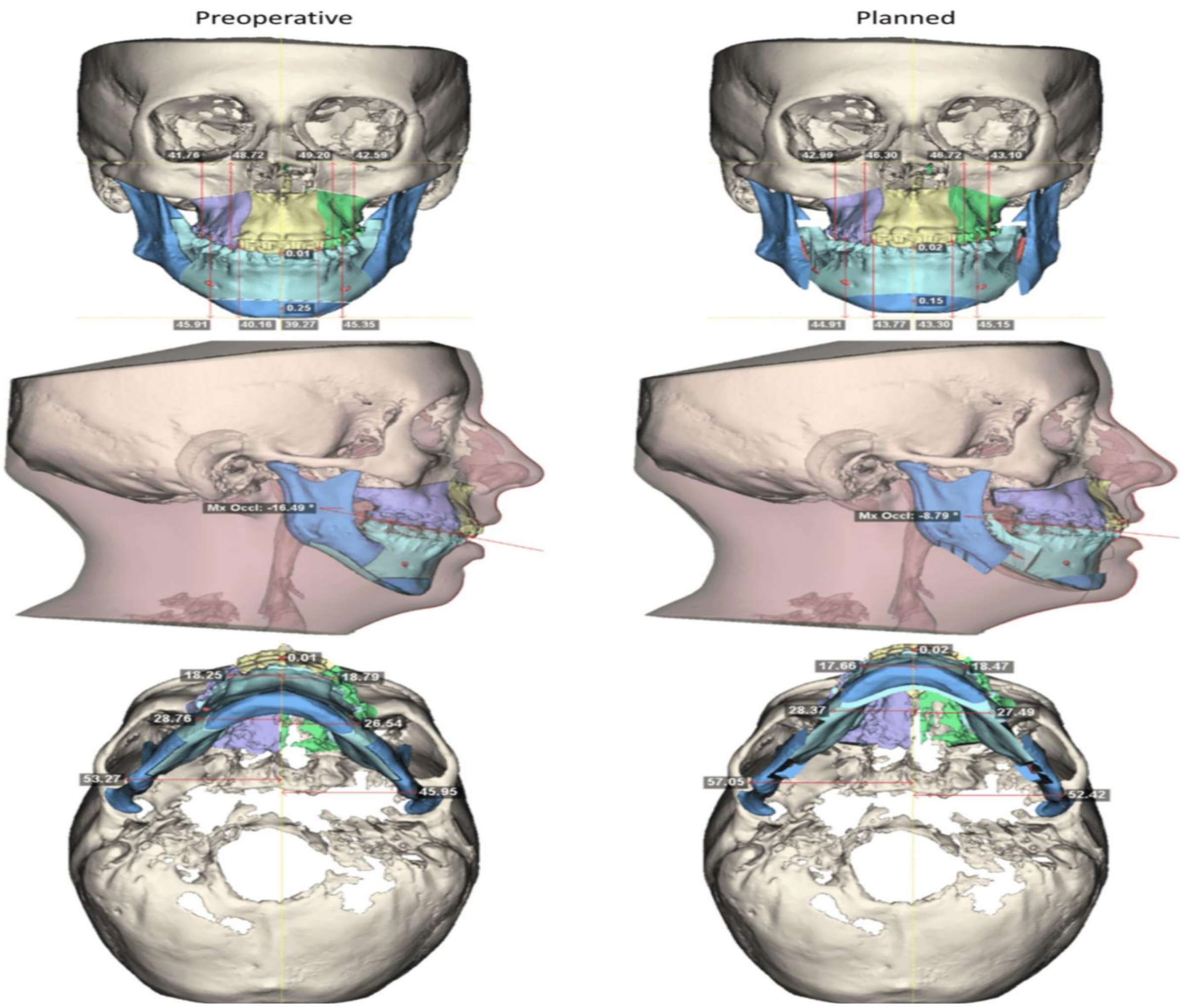
Preoperative
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Mx Occl: -16.49 °
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DISCUSSION

Principal findings

The collected evidence shows that AI reliably automates several discrete planning tasks — notably cephalometric landmarking and CBCT segmentation — delivering substantial time savings and improved inter-operator consistency. Where comparative studies exist (implant planning, small orthognathic series), AI-assisted planning achieves accuracy similar to or slightly better than conventional manual planning while substantially reducing time-to-plan and cognitive load for planners. However, the leap from improved process metrics to demonstrable patient-centered outcome improvements (functional results, long-term stability, complication reduction) has not yet been established by high-quality multicenter randomized trials.

Clinical implications

For practicing OMFS teams, the current best-practice approach is augmented planning: deploy AI for time-consuming, objective tasks (segmentation, landmarking) but retain surgeon oversight for final plan decisions, soft-tissue considerations, and complex judgment calls (airway tradeoffs, occlusal adjustments, biologic constraints). Integration of AI can shorten the planning cycle, increase throughput, and democratize access (less experienced teams can achieve expert-level consistency), but it should be introduced with internal validation and outcome monitoring.

Technical and implementation challenges

Key technical barriers include domain shift across imaging devices, the need for diverse training datasets representative of the patient population, and the integration of AI outputs into secure clinical systems. Explainable AI methods and clear performance metrics (e.g., mean radial error, Dice, plan-to-execution deviation) should be mandatory reporting items in studies. Clinically, institutions must plan for workflow redesign, staff training, and legal governance when adopting AI tools.

Research gaps and recommendations

There is an urgent need for:

1. Prospective, multicenter trials that compare AI-assisted versus conventional planning with patient-centered endpoints (operative time, accuracy of execution, functional and aesthetic outcomes, complication rates).
2. External validation datasets across scanners, ethnic groups and age ranges.
3. Standardized reporting guidelines for AI performance in OMFS (task definition, datasets, ground truth labeling, evaluation metrics).
4. Economic analyses to quantify cost–benefit and return on investment for AI adoption.

Proposed practical adoption framework

We propose a stepwise pathway for centers wishing to integrate AI into OMFS planning:

1. Pilot validation: locally test AI model outputs (segmentation and landmarking) on a retrospective dataset (n≥50) and quantify errors vs expert ground truth.
2. Parallel workflow trial: use AI outputs in parallel with conventional planning for a consecutive series (n≥30), record time savings and concordance, and require surgeon sign-off on final plans.
3. Prospective outcome monitoring: collect operative and patient outcomes for at least 12 months to detect any safety signal.
4. Governance and training: define roles, reporting, and data privacy protocols; provide staff training and patient information materials.

CONCLUSION

Artificial intelligence has matured to the point where it can reliably automate substantial components of OMFS planning, producing meaningful efficiency and consistency gains. Current evidence — strongest for automated cephalometrics, CBCT segmentation and implant planning — supports AI as a complementary tool that can reduce planning time and inter-operator variability while maintaining plan accuracy. However, AI is not yet a replacement for expert clinical judgment: prospective multicenter clinical trials with patient-level endpoints, external validation across devices/populations, and careful regulatory governance are required before fully autonomous planning is acceptable. Centers should adopt AI in a staged, validated manner with continuous outcome monitoring and surgeon oversight.

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Conflicts of interest

The authors declare no conflicts of interest related to this manuscript.

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