Research Article

Artificial Intelligence in Dental Implant Treatment Planning: A Systematic Review

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Abstract

Background: Artificial intelligence (AI) is increasingly being integrated into digital dentistry and dental implantology, particularly for three-dimensional image analysis, anatomical segmentation, implant-site identification, bone assessment, and computer-assisted treatment planning. Because implant placement is prosthetically and anatomically driven, reliable interpretation of cone-beam computed tomography (CBCT) data is central to reducing surgical and prosthetic complications.

Objective: To systematically synthesize current evidence regarding AI applications in dental implant treatment planning, with emphasis on CBCT-based anatomical identification and segmentation, edentulous-site detection, bone-dimension assessment, technical assistance in planning, and emerging outcome prediction.

Methods: Evidence was synthesized from recent systematic reviews, meta-analyses, scoping reviews, and representative primary studies addressing AI-assisted implant planning. The review framework follows PRISMA 2020 principles and organizes evidence according to population, intervention, comparison, outcomes, AI architecture, imaging modality, and clinical application. Because substantial heterogeneity exists in algorithms, datasets, reference standards, and reported endpoints, quantitative pooling was restricted to outcomes already meta-analyzed in the literature.

Results: Published reviews consistently show high technical performance for several CBCT-based tasks. A 2025 systematic review and meta-analysis reported pooled accuracy of 96% for mandibular and 83% for maxillary edentulous-site identification. A 2026 systematic review of 28 implant-planning studies reported anatomical-segmentation accuracy ranging from 66.4% to 99.1%, with 18 studies addressing segmentation and eight examining technical assistance. A 2026 meta-analysis of U-Net-based mandibular-canal segmentation reported pooled Dice similarity coefficient of 0.84 and substantial heterogeneity. AI-assisted systems can markedly reduce segmentation and planning time, but evidence remains dominated by retrospective, single-centre, and technically focused studies.

Conclusion: AI has substantial potential to improve the speed, consistency, and anatomical precision of dental implant treatment planning, particularly when applied to CBCT segmentation and risk-structure identification. Current evidence does not justify autonomous implant planning. External validation, multicentre prospective studies, standardized reporting, explainability, regulatory oversight, and clinician-in-the-loop workflows are required before routine autonomous use.

Keywords: Artificial intelligence; dental implants; implant treatment planning; cone-beam computed tomography; deep learning; convolutional neural network; U-Net; anatomical segmentation; guided implant surgery; digital dentistry.

Introduction

Dental implants have become an established treatment option for replacing missing teeth, but predictable outcomes depend on accurate diagnosis, three-dimensional assessment of available bone, identification of vital anatomical structures, prosthetically driven implant positioning, and careful transfer of the virtual plan to the surgical field. CBCT has become a central imaging modality for implant planning because it provides three-dimensional information about alveolar bone morphology, the mandibular canal, mental foramen, maxillary sinus, nasal floor, and other structures relevant to implant placement.[1]

Digital implant workflows increasingly combine CBCT, intraoral scanning, virtual prosthetic planning, computer-aided design and manufacturing, and static or dynamic computer-assisted surgery. AI adds a further computational layer by enabling automated pattern recognition, image segmentation, classification, prediction, and generation of candidate planning solutions. Deep learning—especially convolutional neural networks (CNNs) and U-Net-derived architectures—has become particularly important for volumetric dental image analysis.[2]

The emerging evidence is encouraging but fragmented. Earlier systematic reviews primarily evaluated implant-type recognition, implant-success prediction, and implant-design optimization, whereas newer reviews increasingly focus on CBCT-based presurgical planning. Recent evidence indicates that AI can identify edentulous regions and anatomical structures with high accuracy and can support planning tasks, but complete automation has not yet been scientifically validated. This distinction is clinically important: a model that accurately segments an anatomical structure is not equivalent to a validated system that can independently prescribe an implant position.[3]

The present review therefore focuses specifically on AI in dental implant treatment planning and emphasizes the translation gap between algorithmic performance and clinically meaningful decision-making.

RESEARCH OBJECTIVES

To summarize AI applications used in preoperative dental implant treatment planning.

To evaluate reported performance for identification and segmentation of teeth, edentulous regions, mandibular canal, maxillary sinus, bone and other relevant structures.

To summarize evidence for AI-assisted technical planning, including implant-position estimation, drilling-protocol assistance and bone assessment.

To compare the maturity of evidence across AI architectures, imaging modalities and clinical tasks.

To identify methodological, ethical, regulatory and clinical barriers to implementation and define priorities for future research.[4]

Materials And Methods

Protocol and reporting framework

The manuscript is structured in accordance with PRISMA 2020 reporting principles , including predefined eligibility criteria, independent screening, data extraction, quality assessment and narrative synthesis.

Focused research question

In patients requiring dental implant treatment, does the use of AI-based image analysis or planning assistance, compared with conventional clinician-based assessment or manual segmentation, improve anatomical identification, planning accuracy, efficiency, or clinically relevant implant-planning outcomes?

TABLE 1. PICOS framework

Component	Definition
Population	Adults or human CBCT/radiographic datasets relevant to dental implant treatment planning.
Intervention	AI, machine learning, deep learning, CNN, U-Net or related computational models used for implant planning or planning-relevant image analysis.
Comparator	Manual expert interpretation, conventional digital planning, conventional radiographic assessment, or clinician-generated plans.
Outcomes	Accuracy, sensitivity, specificity, precision, recall, F1 score, Dice similarity coefficient, IoU, Hausdorff distance, planning time, bone measurements, implant-position parameters, and clinical outcomes.
Study designs	Diagnostic/observational studies, retrospective or prospective clinical studies, randomized studies, systematic reviews and meta-analyses used for evidence synthesis.

Search strategy and evidence sources

The evidence base was cross-checked against recent systematic reviews and meta-analyses indexed in PubMed, including reviews covering AI-driven implant planning, presurgical digital planning, implant dentistry applications, edentulous-site identification, tooth segmentation, mandibular-canal segmentation, implant prognosis, and computer-assisted implant accuracy. The most directly relevant recent review searched PubMed/MEDLINE, Scopus and Web of Science through July 31, 2024 and included 28 studies. Another 2026 systematic review searched

PubMed, Scopus, Google Scholar and Cochrane and included 10 studies focused on CBCT-based AI-assisted implant planning. These published reviews provide the primary evidence anchors for this manuscript.[5]

Eligibility criteria

Included evidence addressed AI applied to dental implant planning or a planning-critical task such as segmentation of teeth, edentulous sites, mandibular canal, maxillary sinus, bone structures or other anatomical landmarks; measurement of bone dimensions; implant-position or drilling assistance; or prediction of implant-related outcomes. Editorials, opinion pieces, educational demonstrations without validation, and studies unrelated to implant planning were not used as primary evidence.

Quality assessment

Quality and reporting limitations were interpreted using tools appropriate to the evidence type, including QUADAS-2 for diagnostic-accuracy studies, PROBAST for prediction models, JBI/CASP-style appraisal for observational and quasi-experimental studies, and CLAIM principles for AI in medical imaging. The published 2026 review of 28 implant-planning studies rated four studies high quality, four medium quality and 20 low quality using a JBI checklist, indicating that technical performance should not be equated with high certainty of clinical evidence.[6]

Data synthesis

Because the included evidence is heterogeneous in AI architecture, reference standard, imaging protocol, dataset size, anatomical target and outcome definition, a single de novo pooled effect estimate was not considered appropriate. Findings were synthesized thematically across: (1) anatomical segmentation; (2) edentulous-site detection; (3) bone assessment; (4) technical planning assistance; (5) implant-position prediction; (6) prognosis/outcome prediction; and (7) clinical implementation, ethics and governance.

Results

Evidence landscape

Recent systematic reviews demonstrate rapid growth in AI research within implant dentistry. A 2025 systematic review of 120 papers reported that deep learning was used in 89.2% of studies, with image data predominating; 72% of image-based studies used two-dimensional data and 28% used three-dimensional data. Eleven studies were judged to have high risk of bias. A separate 2024 scoping review identified 26 studies and reported a mean AI accuracy of 88.7% across implant-dentistry applications.[7]

For the specific treatment-planning question, Zaww et al. identified 28 studies: 18 addressed anatomical segmentation and eight examined technical assistance. Reported anatomical-segmentation accuracy ranged from 66.4% to 99.1%. A newer 2026 systematic review focused on CBCT-based planning identified 10 studies and reported AI performance of 92–99.7% for detection of teeth and edentulous regions, with precision and recall frequently exceeding 90%.[8]

Figure 1. PRISMA-style study-selection flow reproduced from the published 2026 systematic review by Zaman et al.; the counts are not presented as a newly performed search in this manuscript.

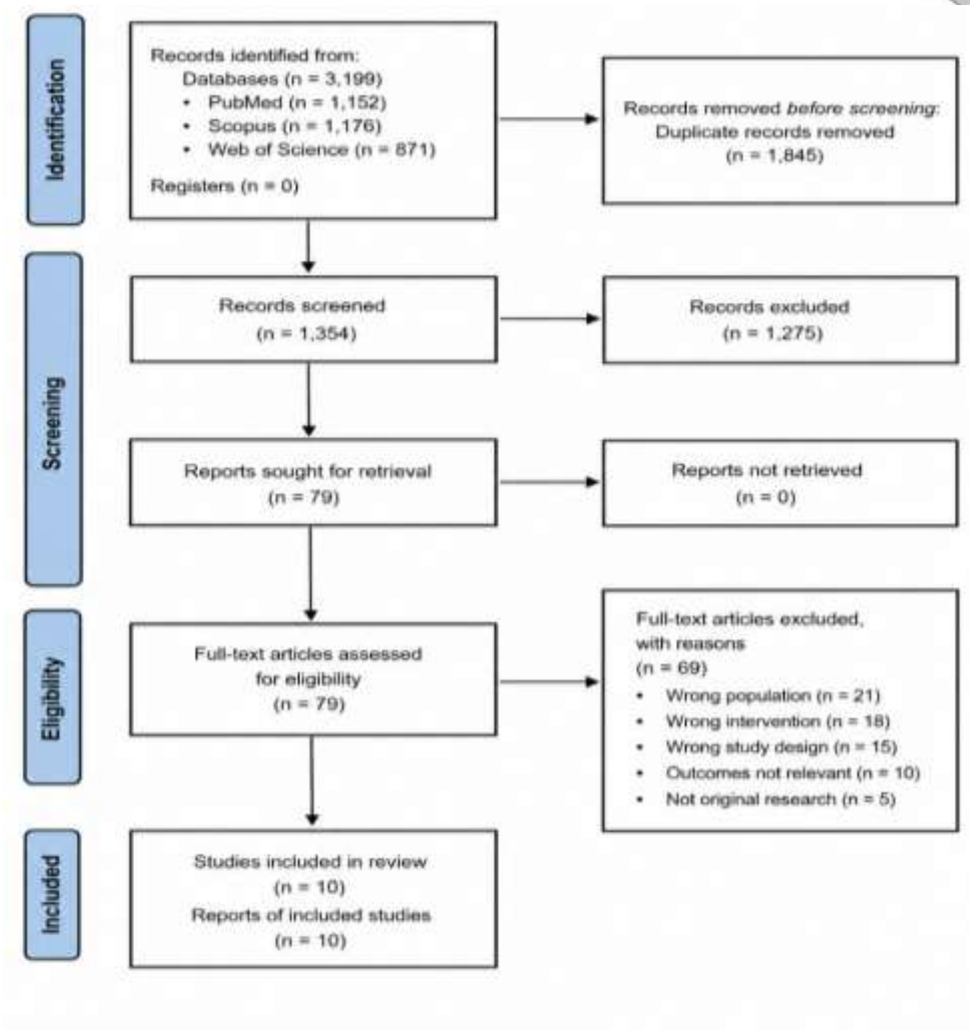


TABLE 2. Representative evidence domains

Evidence domain	Representative evidence	Reported performance	Clinical interpretation
Edentulous-site identification	AI on CBCT	Mandible 96%; maxilla 83% pooled accuracy	Strong technical potential; external validation still needed.
Tooth segmentation	Deep-learning CBCT models	Pooled DSC ≈0.95	Supports automated tooth delineation and planning workflows.
Anatomical segmentation	18 studies in 2026 review	66.4–99.1% accuracy	Performance varies by structure and dataset.
Mandibular-canal segmentation	U-Net meta-analysis	Pooled DSC 0.84; IoU 0.81	Promising, but very high heterogeneity.
Planning assistance	8 studies in 2026 review	High technical potential	Useful as decision support rather than autonomous prescription.

Outcome prediction	AI prognosis literature	Variable across peri-implant and success outcomes	Early evidence; clinical validation limited.

Figure 2. Major evidence domains reported in recent implant-planning reviews

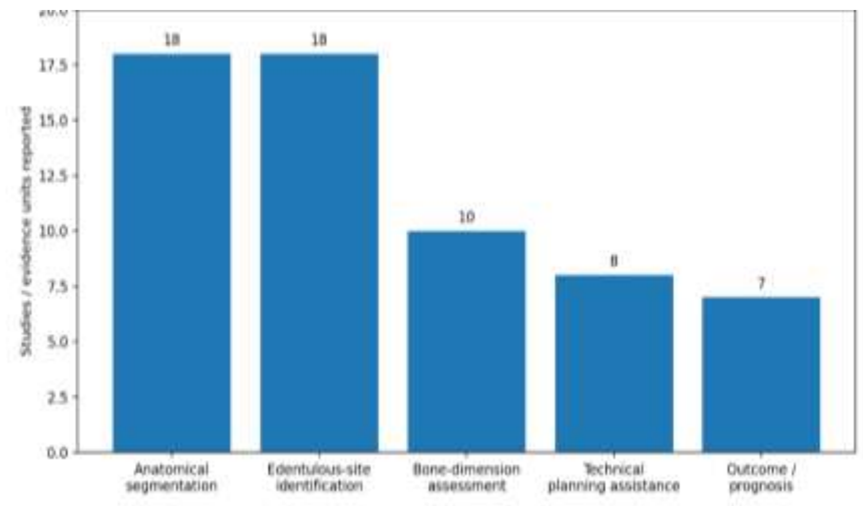
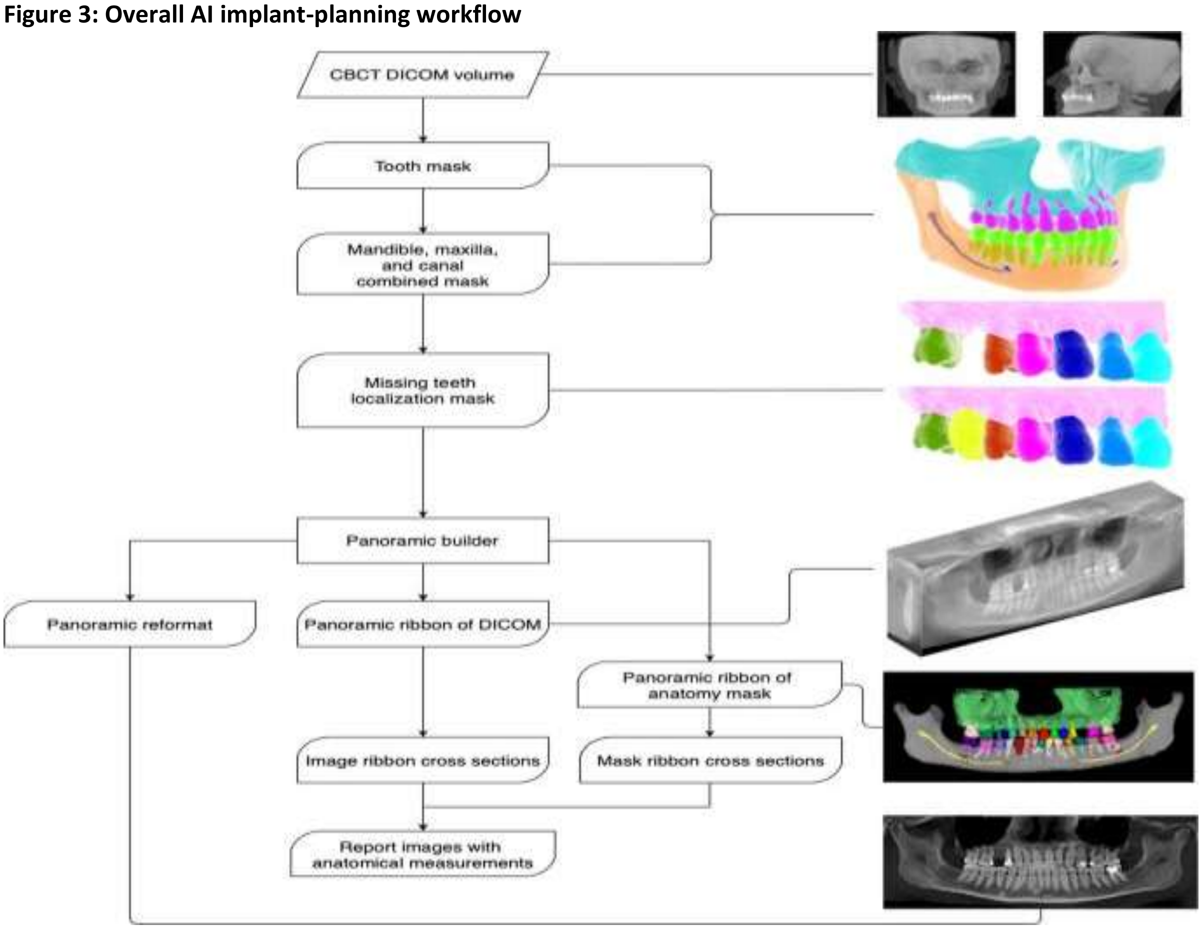


Figure 3: Overall AI implant-planning workflow



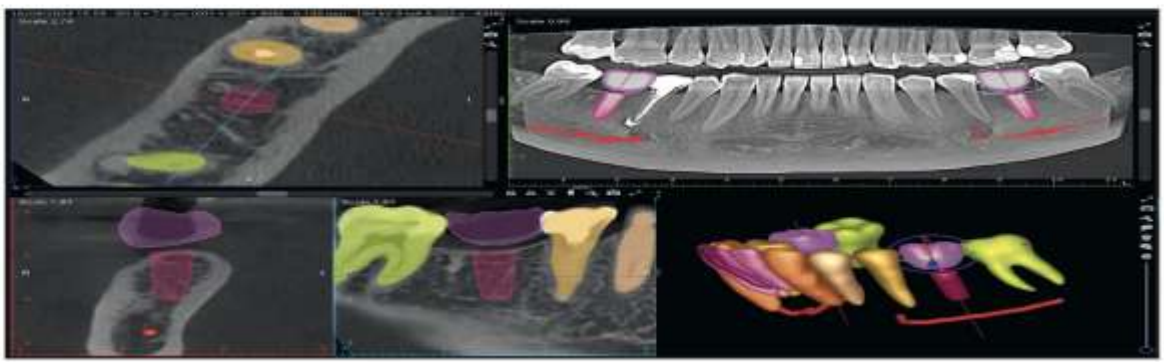
AI-assisted anatomical segmentation

Segmentation is the most mature implant-planning application. AI systems can identify teeth, edentulous regions, alveolar bone, the mandibular canal and other anatomical structures on CBCT volumes. Automated segmentation may reduce repetitive manual annotation and create a consistent anatomical foundation for virtual implant planning.[9]

Tooth segmentation is supported by a 2024 systematic review and meta-analysis reporting a pooled Dice similarity coefficient of 0.95 and segmentation times ranging from approximately 1.5 seconds to 3.4 minutes across included studies. For the mandibular canal, a 2026 meta-analysis of eight quantitatively synthesized studies reported pooled DSC 0.84, IoU 0.81 and 95th-percentile Hausdorff distance of 0.89 mm, with I^2 above 99%, highlighting marked heterogeneity.[10]

These metrics are technically important but clinically incomplete. A high Dice score does not automatically guarantee safe implant placement. Small segmentation errors near the mandibular canal or sinus can have disproportionate clinical consequences, making clinically relevant distance-to-structure and false-negative analyses essential.

Figure 4: CBCT segmentation



Edentulous-region detection and bone assessment

AI can automate detection of missing-tooth regions and estimate bone dimensions that influence implant selection and positioning. The 2025 systematic review and meta-analysis by Alqutaibi et al. found pooled accuracy of 96% for mandibular and 83% for maxillary edentulous-area identification from CBCT. The difference between arches illustrates the importance of anatomical complexity, imaging characteristics and model generalizability.[11]

Recent CBCT studies have also investigated bone-width and bone-height measurements, bone-density estimation, and classification of implant sites. Such systems can support preliminary screening and accelerate the transition from raw imaging to a structured planning environment. However, bone measurements remain dependent on image quality, voxel size, artefacts, segmentation accuracy and the reference standard used.[12]

Figure 5: Edentulous-site/bone assessment

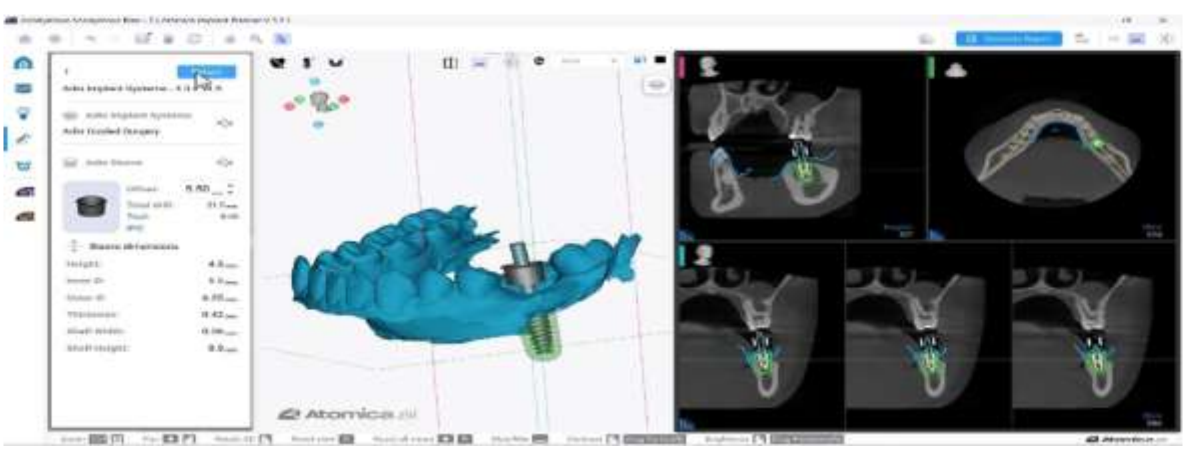
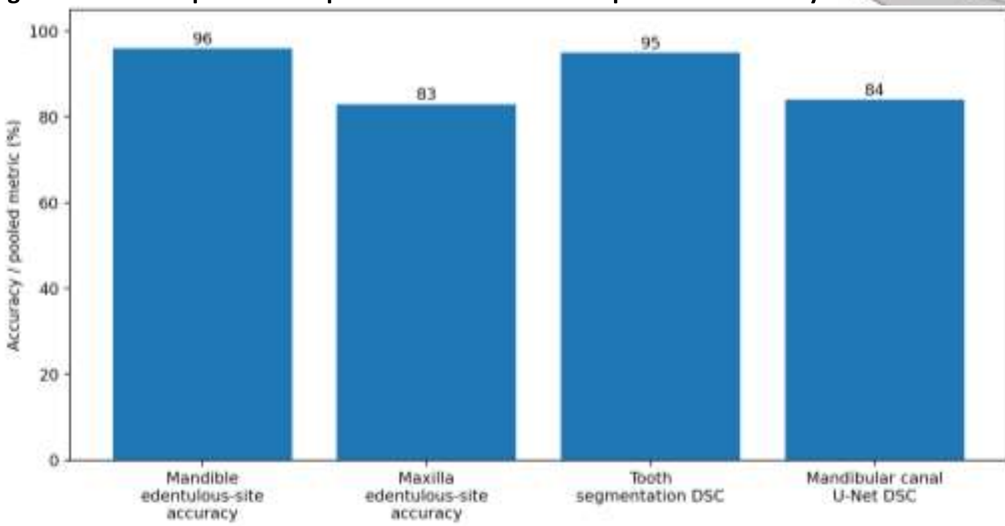


Figure.6 Selected quantitative performance estimates reported in recent systematic reviews/meta-analyses.



Technical planning assistance

Beyond segmentation, AI is being explored for planning-relevant technical decisions. The 2026 systematic review by Zaww et al. identified eight studies addressing technical assistance, including prediction of jawbone mineral density, optimization of drilling protocols, and classification of plans for maxillary sinus augmentation. A separate CBCT-focused review reported AI-generated planning times that were substantially shorter than conventional planning in selected studies.[11,12]

The evidence suggests that AI may be most valuable when it compresses repetitive analytical work while leaving the final clinical decision to the surgeon and restorative team. This model is preferable to autonomous planning because implant selection and position depend on factors that may not be fully represented in imaging data, including restorative space, occlusion, aesthetics, soft-tissue phenotype, patient preferences, systemic risk, hygiene, parafunction and the planned prosthesis.[13]

Implant position prediction and emerging autonomous planning

Recent research has moved from structure recognition toward prediction of implant position, long-axis orientation, length and diameter. ImplantPlanNet, reported in 2026, represents an emerging example of deep learning for automatic initial implant planning from preoperative CBCT in single-tooth missing scenarios. Such systems demonstrate the direction of the field but should be considered experimental until validated prospectively across institutions, scanners, anatomical phenotypes and clinicians.[14]

Importantly, the current literature does not establish that AI can independently determine the clinically optimal implant position in routine practice. The 2024 scoping review of presurgical AI planning explicitly noted that full automation had not been documented or scientifically validated.

Implant prognosis and outcome prediction

AI has also been studied for prediction of implant success, osseointegration, peri-implant bone loss and failure using radiographic and patient-level data.[15] Earlier systematic evidence reported implant-success or osseointegration prediction performance ranging from approximately 62.4% to 80.5%, while newer reviews suggest improving performance but continued methodological limitations. Prognostic models are clinically attractive because they could integrate anatomical and patient-level risk factors, but calibration, external validation and prospective clinical utility remain insufficient.

Prediction should therefore be distinguished from planning. A model that estimates failure risk may inform case selection or maintenance intensity but does not necessarily identify the optimal three-dimensional implant position.[11,15]

Comparison with conventional planning and guided surgery

Computer-assisted implant surgery already improves transfer of virtual plans to the clinical field, although deviations in angle, coronal entry and apical position remain clinically relevant. Systematic reviews of guided surgery report measurable deviations and emphasize the need for safety margins. AI may improve upstream image interpretation and planning, but it cannot eliminate downstream errors introduced by guide manufacturing, registration, patient movement, surgical technique or anatomical changes.[16]

Recent evidence comparing freehand and guided surgery supports the broader principle that digital planning can improve positional predictability. AI should therefore be considered an additional decision-support layer within a validated digital workflow rather than a replacement for guided-surgery quality controls.

Risk of bias and methodological limitations

The strongest recurring limitation across the literature is the mismatch between high technical accuracy and low-to-moderate clinical evidence certainty. Many studies use retrospective datasets, single-centre CBCT archives, limited sample sizes and expert annotations from one institution. Data leakage, unclear patient-level splitting, inconsistent validation strategies and lack of external testing can inflate apparent performance.[17]

The 2026 review of 28 implant-planning studies classified 20 as low quality, four as medium and four as high quality. The broader 2025 systematic review of 120 AI implantology studies identified 11 studies with high risk of bias. The 2026 mandibular-canal meta-analysis also found extreme statistical heterogeneity, emphasizing that pooled performance should not be interpreted without considering differences in scanners, voxel sizes, annotation standards, model architectures and validation protocols.[15,17]

Ethical, legal and regulatory considerations

AI in implant planning involves patient imaging and potentially identifiable health data. Governance must address data privacy, cybersecurity, informed consent, bias, transparency, accountability and the handling of model uncertainty. Patients should not be led to believe that an AI-generated plan is inherently safer or more accurate than clinician judgment.

AI models trained predominantly on one population, scanner type or clinical environment may fail when transferred to other settings. Diversity in training data and external validation are therefore central to patient safety. Clinicians also require sufficient AI literacy to recognize implausible outputs and override the system when clinical context conflicts with the model.[18]

Discussion

The evidence synthesized in the present review indicates that artificial intelligence (AI) is progressively transforming dental implant treatment planning from a predominantly manual and operator-dependent process toward increasingly automated and data-driven digital workflows. The current development of AI in implant dentistry should be considered a gradual continuum rather than a direct transition from conventional planning to fully autonomous treatment. At present, the strongest evidence is concentrated in image interpretation, anatomical recognition, segmentation, classification, and quantitative assessment.[19] These applications are particularly relevant to dental implantology because CBCT generates complex three-dimensional datasets containing information about teeth, alveolar bone, mandibular canal, mental foramen, maxillary sinus, nasal cavity, and edentulous regions. Deep-learning models can process these datasets rapidly and generate standardized anatomical representations that can subsequently support virtual implant planning.[20]

Anatomical segmentation represents one of the most established applications of AI in implant planning. Manual identification and tracing of anatomical structures can be time-consuming and may be influenced by clinician experience, fatigue, image quality, and interobserver variability. AI-assisted segmentation has the potential to reduce these limitations by providing rapid and reproducible delineation of clinically relevant structures. This can be particularly valuable for identifying structures that must be protected during implant surgery, such as the mandibular canal and maxillary sinus. Nevertheless, automated segmentation should be considered an aid to clinical interpretation rather than a substitute for expert evaluation. Even a small segmentation error close to a vital anatomical structure may have greater clinical significance than a larger error in an anatomically irrelevant region.[21]

The evidence becomes considerably less mature when AI progresses from recognition to recommendation. Identifying the mandibular canal or an edentulous region is fundamentally different from deciding where an implant should ultimately be positioned. Implant positioning requires integration of anatomical, prosthetic, biological, functional, and aesthetic factors. These include residual ridge morphology, bone height and width, proximity to vital structures, implant dimensions, prosthetic space, emergence profile, occlusion, soft-tissue characteristics, periodontal status, aesthetic requirements, patient-related risk factors, and the planned prosthetic restoration. Therefore, high image-segmentation accuracy should not automatically be interpreted as evidence that an AI system can independently determine the optimal implant position.[22]

This distinction emphasizes the importance of using clinically meaningful outcomes when evaluating AI systems. Most existing studies report technical performance measures such as accuracy, sensitivity, specificity, precision, recall, Dice similarity coefficient, intersection-over-union, or Hausdorff distance. Although these parameters are essential for evaluating algorithmic performance, they do not directly demonstrate clinical benefit. Future studies should therefore assess whether AI-assisted planning improves implant-position accuracy, reduces deviations from the planned implant axis, decreases the risk of damage to anatomical structures, reduces surgical and prosthetic complications, improves peri-implant health, decreases planning time, and ultimately improves long-term implant survival and patient satisfaction.[23]

Another important finding is that efficiency may be as important as accuracy. Conventional implant planning involves multiple sequential steps, including CBCT assessment, anatomical identification, segmentation, bone measurement, identification of risk structures, virtual implant positioning, and modification of the proposed plan. AI can potentially automate several repetitive components of this process and thereby reduce planning time. Automated segmentation and preliminary anatomical mapping may allow clinicians to reach the decision-making stage more rapidly. This may be particularly beneficial in complex cases involving multiple implants, extensive bone resorption, anatomical limitations, or multidisciplinary restorative requirements.[24]

However, efficiency should never compromise verification. An AI system may analyze a CBCT dataset within seconds, but rapid processing does not guarantee a clinically correct output. A faster incorrect plan remains unsafe. For this reason, AI-generated segmentation, measurements, risk alerts, and implant proposals should undergo systematic clinician verification before they are incorporated into the final treatment plan. The level of verification should increase when image quality is poor, metallic artefacts are present, anatomy is unusual, or the proposed implant is close to a vital anatomical structure.[22,25]

The findings therefore support the concept of clinician-in-the-loop AI as the most appropriate current implementation model. Under this approach, AI performs computationally intensive tasks such as anatomical segmentation, measurement, risk-structure identification, and generation of preliminary implant proposals, while the clinician retains responsibility for interpretation and final treatment decisions. The clinician can accept, modify, or reject AI-generated outputs according to the patient's clinical and prosthetic requirements. This approach preserves the advantages of automation while maintaining professional judgment and accountability.[26]

Clinician-in-the-loop systems may also help address uncertainty and automation bias. Future AI systems should ideally indicate the confidence associated with their predictions rather than providing an apparently definitive output. Low-confidence predictions could trigger additional clinician review, particularly in cases involving motion artefacts, low image quality, unusual anatomy, or inadequate representation in the training dataset.[27] This is important because clinicians may develop excessive confidence in computer-generated recommendations when they are presented within highly sophisticated digital interfaces. Appropriate AI education should therefore include recognition of model limitations, interpretation of uncertainty, identification of implausible outputs, and the ability to override automated recommendations.[27,28]

A major limitation of the current evidence is the substantial heterogeneity between studies. Differences in CBCT scanners, voxel sizes, image quality, patient populations, anatomical characteristics, annotation methods, reference standards, AI architectures, and validation protocols make direct comparison difficult. A model that performs exceptionally well on a single institutional dataset may not demonstrate the same performance when applied to images obtained from another scanner, institution, or patient population. External and multicentre validation should therefore become a major priority.[29] Prospective studies are particularly important because they can determine whether AI maintains its performance when incorporated into real-world clinical workflows.[30]

Future AI systems may also benefit from multimodal treatment planning. CBCT provides detailed information about three-dimensional bone anatomy and vital structures, whereas intraoral scans provide information about teeth, soft-tissue contours, occlusion, and restorative surfaces. Combining these datasets with facial scans, prosthetic designs, periodontal measurements, and patient-related clinical information could allow AI systems to develop more comprehensive prosthetically driven planning solutions. Such systems may eventually generate several candidate treatment strategies and allow clinicians to compare them according to anatomical safety, restorative requirements, biological considerations, expected prognosis, and patient preferences.[31]

Figure 7: Clinician-in-the-loop AI workflow

Ethical and regulatory considerations will become increasingly important as AI becomes more deeply integrated into clinical decision-making. Patient CBCT scans and clinical records represent sensitive health information and therefore require appropriate privacy protection, cybersecurity, data governance, and access control. In addition, responsibility for an incorrect AI-generated treatment plan cannot simply be transferred to the algorithm. Until autonomous systems have demonstrated adequate safety, validation, and regulatory acceptance, the clinician must remain responsible for reviewing and approving the final plan.[32]

Overall, the evidence supports a cautious but optimistic interpretation of AI in dental implant treatment planning. AI has already demonstrated considerable potential for anatomical recognition, segmentation, quantitative assessment, and workflow automation. However, the transition from image recognition to autonomous clinical decision-making remains considerably more challenging. The most appropriate current role of AI is therefore as an intelligent decision-support system that augments rather than replaces clinical expertise. Future research should prioritize prospective multicentre validation, standardized datasets, clinically meaningful outcomes, explainable AI, uncertainty estimation, human–AI interaction studies, and evaluation of long-term clinical outcomes. The ultimate objective should not simply be to develop algorithms with higher accuracy, but to determine whether AI-assisted implant planning can provide safer, faster, more reproducible, and more individualized treatment for patients.[33]

Clinical Implications

AI-assisted CBCT segmentation can reduce repetitive manual work and standardize identification of planning-relevant structures.

Automated edentulous-site detection and bone assessment may improve workflow efficiency, particularly in complex or multiple-implant cases.

AI-generated implant proposals should be treated as preliminary decision support rather than prescriptions.

Final implant position should be verified against prosthetic, periodontal, surgical and anatomical requirements.

Clinicians should document AI use, retain the final clinician-approved plan and maintain conventional safety margins around vital structures.

AI performance should be monitored after deployment because model performance can drift when scanners, populations or workflows change.[34]

Future Research Directions

Large multicentre CBCT datasets with standardized voxel-size reporting and expert consensus annotations.

Prospective clinical trials comparing AI-assisted and conventional planning using clinically meaningful outcomes.

External validation across institutions, countries, scanner manufacturers and patient phenotypes.[35]
Standardized reporting using CLAIM and related AI-specific reporting frameworks.
Calibration and uncertainty reporting rather than accuracy alone.
Direct measurement of clinical endpoints including surgical complications, positional deviations, prosthetic complications, peri-implant health and long-term implant survival.[36,37]
Human-AI interaction studies assessing automation bias, clinician trust and override behavior.
Transparent regulatory pathways for adaptive AI systems used in implant planning.[38]

Limitations Of This Review

This manuscript is intentionally transparent about its evidence-generation boundary. It is based on published systematic reviews, meta-analyses, scoping reviews and web-verified primary evidence rather than a newly registered review protocol with independent dual-reviewer database exports.[39] Therefore, the study-selection numbers from published reviews should not be interpreted as the results of a new independent search. Overlap between systematic reviews is also possible. A formal submission should replace this draft's evidence framework with the authors' own reproducible database searches, deduplication file, screening records, risk-of-bias forms and final included-study list.[40]

Conclusion

Artificial intelligence is emerging as a powerful adjunct to dental implant treatment planning, particularly for CBCT-based anatomical segmentation, edentulous-site detection, bone assessment and planning assistance. Current evidence demonstrates high technical performance in several tasks, including pooled mandibular edentulous-site identification and automated mandibular-canal segmentation. Nevertheless, the evidence base is characterized by heterogeneity, limited external validation, retrospective designs and inconsistent reporting. The clinical future of AI in implantology is therefore most likely to involve intelligent clinician-in-the-loop systems that accelerate analysis and provide reproducible decision support while preserving human responsibility for diagnosis, treatment selection and patient safety.

TABLE 3. Key advantages and limitations of AI in implant planning

Potential advantage	Current limitation	Research priority
Rapid segmentation	Performance varies by anatomy and imaging protocol	External multicentre validation
Consistent anatomical mapping	Dependence on annotation quality	Consensus annotation standards
Reduced planning time	Efficiency does not equal clinical safety	Prospective workflow trials
Candidate implant-position generation	Prosthetic and biological context may be incompletely represented	Human-AI comparative studies
Risk prediction	Calibration and generalizability remain uncertain	Prospective prognostic validation
Scalability	Data governance and interoperability barriers	Standardized datasets and regulatory frameworks

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