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Artificial Intelligence in Digital Implant Planning: A Narrative Review of Current Trends and Future Prospects

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Abstract

Background: Artificial intelligence (AI) has emerged as a streaming technology in dental implant planning that addresses workflow complexity and enhances diagnostic precision across multiple treatment stages. **Objective:** This narrative review synthesizes current evidence on AI applications throughout the implant planning continuum, examining accuracy metrics, clinical implementation considerations, and future directions. **Methods:** In 2015-2025, AI applications in implant dentistry, including anatomical segmentation, virtual patient creation, presurgical planning, computer-assisted surgery, prosthetic design, and outcome prediction, were examined. **Results:** AI demonstrates high accuracy in anatomical segmentation (>90%), edentulous site identification (96% mandibular accuracy, 83% maxillary accuracy), and virtual implant placement (95% clinical acceptability). Compared with human clinicians, deep learning models automate labor-intensive processes, reduce the segmentation time from hours to seconds, and achieve expert-level planning with 2.2-fold faster execution. Compared with conventional guided approaches (1.0 mm), robotic-assisted surgery powered by AI achieves superior positional accuracy (0.5 mm coronal, 0.5 mm apical deviation). AI-powered CAD/CAM systems enhance prosthetic design efficiency and customization. However, significant limitations persist: data heterogeneity reduces generalizability, interference from metal artifacts degrades segmentation, algorithmic opacity undermines clinical trust, and external validation studies remain insufficient. Ethical concerns regarding data privacy, algorithmic bias, and healthcare disparities require careful consideration. **Conclusions:** AI functions most effectively as a clinical decision support system that augments human expertise rather than replacing clinician judgment. Emerging technologies, including explainable AI frameworks, augmented reality visualization, and hybrid models, promise enhanced clinical integration. Prospective multicenter trials with standardized metrics and transparent validation are essential before widespread clinical deployment. AI-augmented implant planning represents a paradigm shift toward precision, personalized, and predictable implant dentistry.

Keywords: Artificial intelligence, dental implants, implant planning, deep learning, computer-assisted surgery, clinical decision support, surgical accuracy

1. Introduction

The digitalization of dental workflows represents one of the most significant paradigms shifts in contemporary implant dentistry[1]. Digital technologies now facilitate comprehensive treatment planning, from initial data acquisition through final prosthetic design, offering substantial improvements in predictability and clinical outcomes[2,3]. This integration encompasses multiple technologies, including cone-beam computed tomography (CBCT) for three-dimensional anatomical visualization, intraoral scanners (IOSs) for capturing dental and soft tissue geometry, facial scanning for aesthetic planning, and computer-aided design/computer-assisted manufacturing (CAD/CAM) systems for prosthetic fabrication[4,5]. These multimodal digital systems enable customized implant planning, supporting innovations, such as patient-specific implants, personalized titanium meshes for guided bone regeneration, and CAD/CAM scaffolds for bone augmentation, ultimately allowing clinicians to transition from generic protocols toward individualized treatment strategies[6,7].

However, the complexity inherent in these digital workflows presents significant challenges. Multiple sequential steps, encompassing image acquisition, multimodal image registration, anatomical landmark identification, segmentation of critical structures, implant position planning, and prosthetic design, require substantial operator expertise and remain time-consuming and user-dependent processes[8]. The extended duration and technical complexity of these workflows can limit their accessibility and consistency across clinical practices, necessitating approaches to streamline procedures and reduce the training burden on clinicians[9].

Artificial intelligence (AI) has emerged as a supportive force in dental implant planning, fundamentally reshaping diagnostic workflows, treatment predictability, and surgical precision[8]. AI techniques, particularly deep learning methodologies grounded in artificial neural networks, offer promising solutions to address these workflow limitations[10]. AI systems have the capacity to automate repetitive tasks, enhance diagnostic accuracy, reduce human error, and improve procedural efficiency, thereby potentially minimizing complications and optimizing treatment outcomes[11]. The significance of AI in implant dentistry extends beyond simple task automation; these technologies can extract complex patterns from imaging data[12], facilitate rapid and consistent anatomical structure segmentation[13], and support evidence-based clinical decision-making at multiple treatment stages[14–20].

Previous studies have documented the potential of AI models in specific implant dentistry applications, including dental implant recognition[21], peri-implant bone loss detection[22], implant failure prediction[23], and automated assessment of bone dimensions for implant site selection on CBCT images[24]. Currently, the scientific literature has comprehensive evidence regarding how AI can be strategically integrated throughout the presurgical implant planning process. This necessitates a detailed analysis of specific treatment planning steps, how AI technologies can increase planning accuracy and efficiency, and what clinical outcomes result from AI-augmented planning compared with conventional approaches. This narrative review addresses these questions by synthesizing current evidence on AI applications across the implant planning continuum, examining reported accuracy metrics, discussing implementation considerations for clinical practice, and identifying future research directions and clinical opportunities. This narrative review synthesizes current evidence on AI applications throughout the implant planning continuum, from anatomical assessment to outcome prediction, while examining accuracy metrics, clinical implementation challenges, and future directions.

2. The role of the AI in anatomic landmark segmentation

The initial phase of digital implant planning focuses on generating 3D virtual reconstructions of dentomaxillofacial structures from CT or CBCT scans. These digital models are essential for virtual surgical planning and designing patient-specific components, such as surgical guides and prostheses[5]. Traditionally, segmentation is performed manually, which is labor intensive and requires significant anatomical and imaging expertise [25]. To reduce time and workload, semiautomatic segmentation methods have been introduced. These rely on defining threshold values of Hounsfield or grayscale intensities to differentiate between tissues [26]. Although semiautomatic processes allow quicker segmentation, they are prone to certain limitations, such as a steep learning curve, the need for excessive manual postprocessing in the presence of high-density material artifacts, and interobserver variability due to manual threshold value selection that differs for each patient and anatomical region, depending on the bone density [27].

Recent advances in AI (Figure 1) have emerged as powerful alternatives to these traditional methods. Modern AI algorithms, especially deep learning models such as convolutional neural networks (CNNs) and U-Net architectures, can automatically segment complex structures with high precision[28]. Their performance is typically evaluated via metrics such as accuracy, recall, precision, Dice score, and intersection over union (IoU), with most studies reporting results exceeding 90% accuracy for CBCT-based segmentation of the mandible, maxilla, teeth, nerves, dental implants, and airway spaces [29–47].

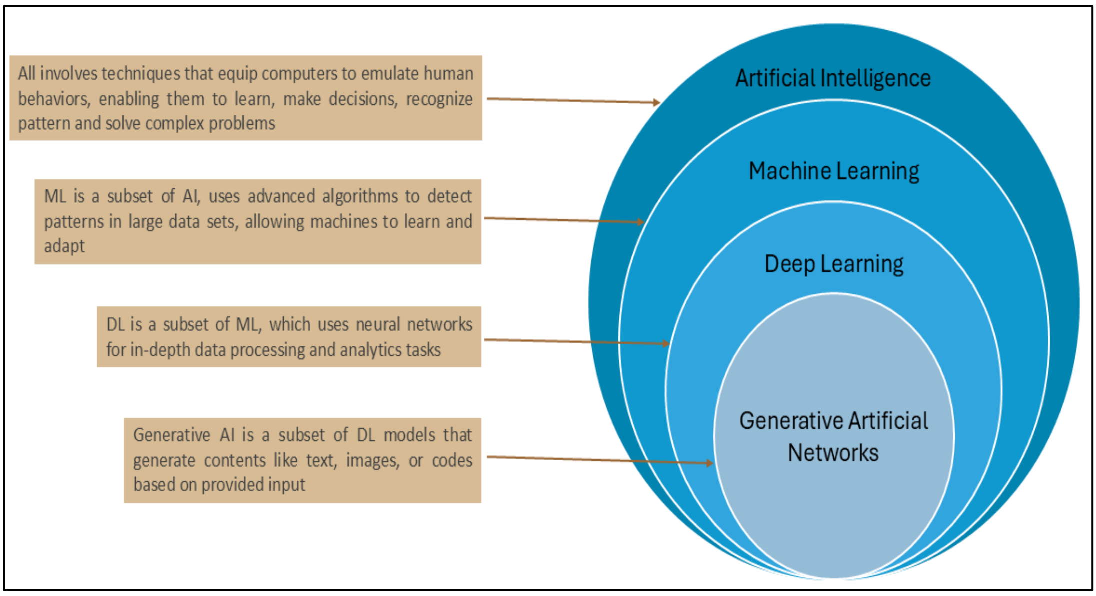

Figure 1. Artificial intelligence model types and their evolution.

Compared with manual or semiautomatic methods, AI segmentation is faster, more consistent, and independent of observer variability; in fact, segmentation tasks that once took clinicians up to several hours can now be completed within seconds [30,38]. Additionally, AI demonstrates robustness in cases affected by metal artifacts, accurately distinguishing anatomical structures even under low-contrast conditions [48].

The integration of AI into cloud-based platforms has further simplified clinical workflows by eliminating the need for high-performance computing hardware [29]. These automated systems increase the efficiency of computer-assisted surgical planning (CASP) in fields such as dental implantology, orthognathic surgery, and navigational procedures. Nevertheless, challenges persist regarding generalizability; AI models may perform inconsistently across data from different scanners and imaging protocols. To overcome this limitation, large, multicenter datasets are needed to train and validate algorithms for broader clinical applicability [49]. Figure 2 shows an example of a cloud-based AI platform that automatically segments anatomical structures from uploaded 3D data of patients.

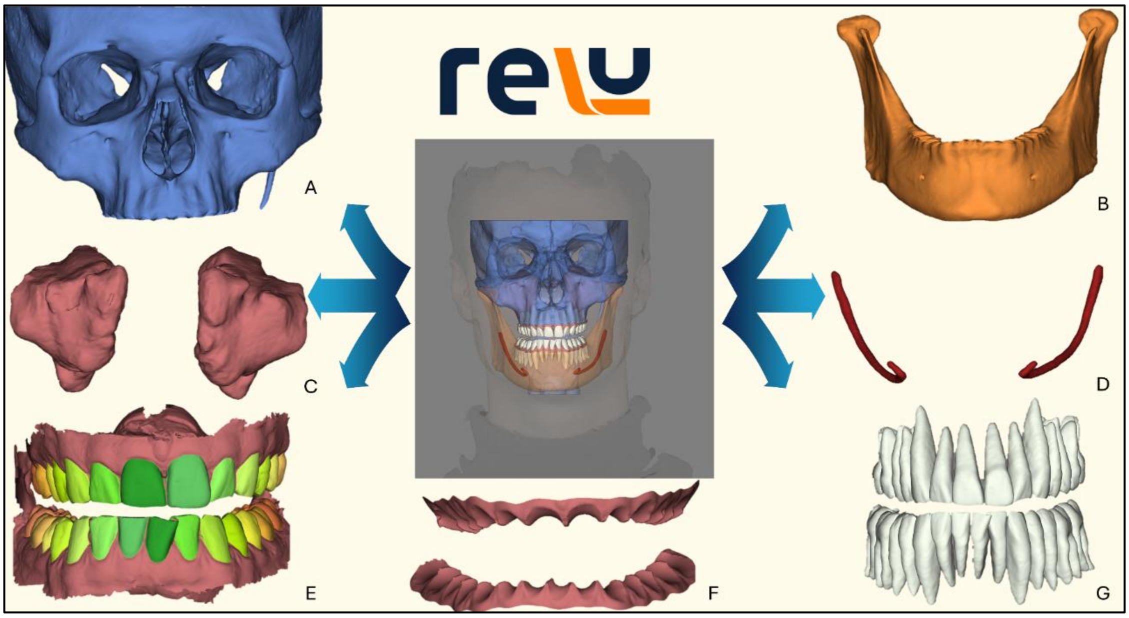

Figure 2. Example of a cloud-based AI platform for automatic anatomical segmentation from CBCT and the IOS. A) Maxillary complex segmented model, B) segmented model of the mandible, C) bilateral maxillary sinus segmented model, D) bilateral mandibular nerve segmentation, E) teeth segmentation from the IOS, F) gingiva segmentation from the IOS, and G) teeth crowns from the IOS fused with roots from CBCT.

3. Virtual patient creation

Image registration is the superimposition of three-dimensional images from different imaging modalities into a unified coordinate frame. It has become fundamental to CASP in oral and maxillofacial procedures. Accurate registration ensures optimal alignment of anatomical structures, preventing misalignments that could compromise surgical outcomes[50]. By combining complementary imaging modalities, such as CBCT, intraoral scanners, and facial scans, clinicians gain comprehensive views of both osseous and soft tissue anatomy, which is essential for successful implant placement, orthognathic surgery, and maxillofacial reconstruction[51,52].

Conventional registration approaches employ either extrinsic methods, which rely on physical markers or fiducial devices placed on the patient during imaging, or intrinsic methods, which identify anatomical or mathematical landmarks for alignment. Although established, these traditional techniques are hindered by substantial drawbacks: metal artifacts obscure critical anatomical details, manual registration demands considerable time investment, and outcomes depend heavily on operator expertise, introducing variability and observer bias. These limitations have prompted a shift toward automated and AI-driven solutions[48,53].

Recent advances in AI have revolutionized image registration by automating previously labor-intensive processes. AI-based registration algorithms now achieve accuracy comparable to or exceeding that of manual landmark-based approaches, with landmark distance errors reduced to less than 0.5 mm and superior performance over existing software algorithms, reducing error distances by 30–70%[54]. The integration of AI-aided segmentation with registration has proven particularly effective; automated registration of CBCT-derived panoramic images with optically scanned dental models yields landmark and surface deviations as low as 0.5 mm, substantially better than manual methods, which typically exceed 1 mm[55]. These advances address longstanding limitations, including labor intensiveness and observer variability, while dramatically improving robustness against metal artifacts and image distortions.

The creation of reliable 3D virtual patient models from CBCT, IOS, and face scans represents a cornerstone of modern surgical planning. Studies have demonstrated that integrated CNN-based segmentation can simultaneously process multiple anatomical structures from CBCT, IOS, and face scans with exceptional precision, achieving Dice similarity coefficients of 99.3% and requiring minimal manual refinement[13,56]. Furthermore, automated fusion of CBCT-derived dental roots with intraoral scanner-derived crowns has proven both robust and clinically efficient, operating over 30 times faster than manual fusion approaches while maintaining accuracy well below 1 voxel in surface discrepancies[57].

AI-powered registration tools offer clear clinical advantages by delivering accurate, rapid, and reproducible multimodal image alignment, eliminating the need for specialized technical expertise [51,52]. These capabilities are essential for planning treatment procedures, designing patient-specific surgical guides and implant-supported restorations, where precision directly impacts functional and aesthetic outcomes. The convergence of advancing algorithms, validated computational tools, and demonstrated clinical utility suggest that automated registration will become standard practice in digital dentistry and maxillofacial surgery. As these technologies mature and gain wider acceptance, they promise to reduce manual workload, minimize operator-dependent variability, and ultimately enhance patient outcomes through precise, standardized surgical planning.

4. Presurgical dental implant planning

AI models have extended beyond anatomical mapping to predict optimal surgical protocols on the basis of bone characteristics. Machine learning algorithms can analyze CBCT images to predict jawbone mineral density and recommend appropriate drilling protocols, achieving accuracy rates of 93.8%, with area under the curve (AUC) values exceeding 0.98[58,59]. This capability enables clinicians to predict bone quality and adjust surgical approaches before making an incision, potentially enhancing primary implant stability and reducing intraoperative complications.

For edentulous site assessment, pooled meta-analytic data indicate 96% accuracy (95% CI: 94–98%) for mandibular implant planning and 83% accuracy (95% CI: 82–84%) for maxillary planning via AI-based detection systems[60]. These measurements encompass bone height and width determinations that directly inform implant size selection and positioning. Notably, AI measurements of bone height in premolar and molar regions show no statistically significant differences compared with manual expert measurements, validating their clinical reliability[24].

The integration of AI into digital implant workflows (Figure 3) enables truly prosthetically driven treatment planning by merging CBCT data with intraoral scans to visualize ideal implant positioning relative to the planned restoration.

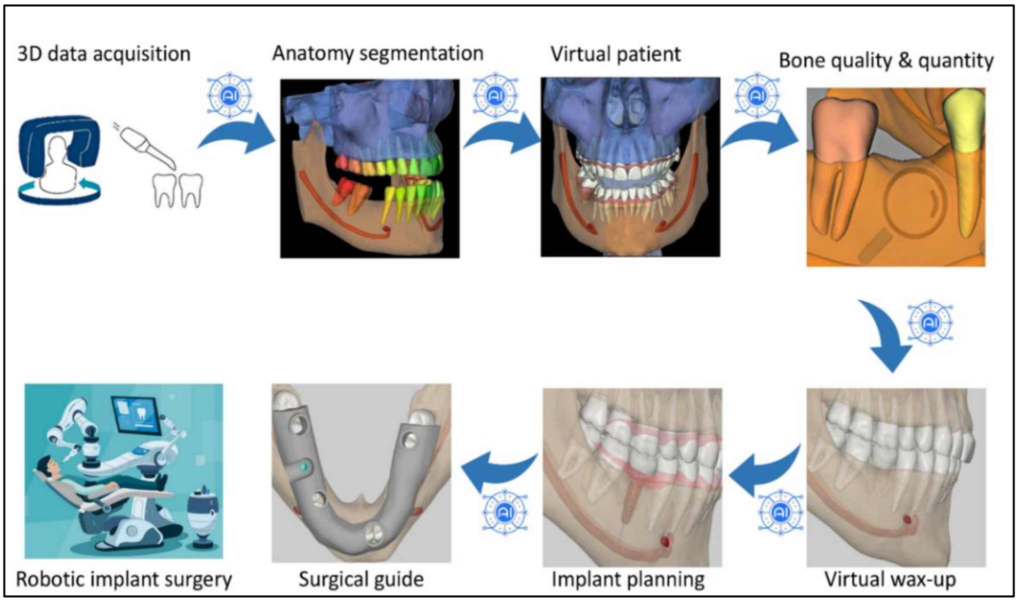

Figure 3. Traditional artificial intelligence-enhanced digital workflow for digital implant planning.

Compared with the HI-based method, AI achieves expert-quality, clinically acceptable single-implant planning (Figure 4) with greater time efficiency and consistency[11]. AI-powered automated virtual implant placement tools have been rigorously evaluated against human experts in preclinical studies[61–63]. These AI systems complete implant planning in approximately 198 seconds compared with 435 seconds for human planners, a 2.2-fold improvement in time efficiency. Remarkably, 95% of AI-generated plans require no significant modifications, nearly matching the 96% clinical acceptability rate of human-generated plans[61,64].

Figure 4. AI-driven digital implant planning for a single maxillary right canine. The AI-based platform first A) segments the anatomical structures followed by B) designing wax-up to follow the concept of prosthetically driven implant planning; then, C) the implant is planned on the basis of the available bone analysis and wax-up design; additionally, the platform designs a temporary crown for provisionalization starting from D) detecting the emergence line for the prosthesis, E) selecting the appropriate abutment, and F) designing the final crown; finally, after treatment approval by the clinician, the platform designs a surgical guide to transfer the digital planning to the real world.

Current evidence demonstrates that AI can achieve expert-level, clinically acceptable implant planning; however, the translation of these plans into surgical execution remains underexplored. Existing studies have focused primarily on static-guided demonstrations with limited quantification of placement accuracy and few evaluations of safety or prosthetic outcomes[61,65,66]. Moreover, most validation has been restricted to single posterior mandibular implants, leaving the generalization of AI planning to anterior, maxillary, immediate, and multi-implant scenarios untested.

Future research should bridge the gap between AI planning and clinical execution through well-designed prospective studies. Key priorities include determining whether AI-generated plans achieve noninferior accuracy and safety compared with clinician plans; assessing how reliably different execution modalities, static guides, navigation, and robotics can be used; transferring the same AI plan to the patient; and quantifying the impact of local registration errors on surgical deviation. Long-term registries should capture outcomes in complex and varied indications, whereas uncertainty-aware AI models that integrate real-world tolerances should be tested for their potential to increase safety without compromising prosthetic precision. Standardized definitions, metric reporting, and transparent error budgets are essential to ensure comparability across studies. Together, these initiatives will enable a rigorous, end-to-end validation of AI-driven implant workflows, linking digital planning accuracy to surgical safety and long-term restorative success.

5. Computer-assisted and robotic implant surgery

Computer-assisted implant surgery (CAIS) has become a major innovation in implant dentistry, improving the precision, predictability, and safety of implant placement by accurately transferring virtual plans into the patient's oral environment[9]. Guided systems are classified as static or dynamic. In static CAIS, prefabricated 3D-printed guides containing metal sleeves and depth stops direct drilling to the planned osteotomy site. Teeth, mucosa, or bone may support these guides and can be designed as single-piece or stackable systems to accommodate complex procedures such as ostectomy or sinus floor elevation [67].

In contrast, dynamic CAIS functions similarly to GPS navigation, using stereoscopic cameras to continuously track fiducial markers on the patient and handpiece, displaying the real-time drill trajectory on CBCT images[68]. Unlike static systems, dynamic navigation does not require a physical template and provides an unobstructed surgical field, enabling intraoperative adjustments and enhanced soft-tissue management. Modern navigation systems integrate both surgical and prosthetic considerations, aiming for site-specific accuracy and immediate provisionalization to improve functional and aesthetic outcomes [69].

The next evolution, robot-assisted computer-aided implant surgery (r-CAIS), incorporates AI, machine vision, sensor fusion, and 3D visualization to further reduce deviations between planned and executed implant positions [70,71]. Robotic systems operate across defined autonomy levels, from semiactive, operator-controlled arms (Level 1) to autonomous systems (Level 2, ADIR) capable of performing osteotomy and implant placement independently [72,73]. In autonomous mode, the robotic arm follows a predefined path within an infrared-guided visual field, executing drilling and implant insertion with visual-force feedback to maintain precision while minimizing operator variability[72].

Recent clinical studies have confirmed the superior accuracy of AI-driven robotic systems, reporting mean coronal deviations of approximately 0.5 mm, apical deviations of 0.5 mm, and angular deviations near 1°, significantly outperforming both static and dynamic guided approaches, which typically show platform deviations of approximately 1.0 mm and angular errors of 3–4° [74–77]. These results demonstrate the potential of autonomous robotics to standardize implant placement accuracy across jaw types and anatomical sites, representing a critical step toward fully digital, precision-guided implantology.

6. The role of AI in prosthetic design and occlusion

AI-powered CAD/CAM systems have transformed dental crown and implant restoration workflows by automating the design process through deep learning and advanced 3D modeling[78]. Platforms such as 3Shape Automate (3Shape A/S, Denmark), Fastdesign.io (Glidewell, USA), Dentbird (Imagoworks, Inc., Republic of Korea), Relu automate (Relu BV, Belgium), and Exocad AI Design (Exocad GmbH, Germany) use neural networks trained on extensive datasets of expert-designed crowns to identify margins, segment teeth, and generate restorations within minutes. These systems achieve high first-fit accuracy, minimize chairside adjustments, and significantly reduce turnaround times, enabling same-day or next-day delivery of precisely milled crowns[79].

Beyond efficiency, AI enhances customization and aesthetic optimization by analyzing patient-specific factors such as facial structure, gum lines, occlusion, and ethnic traits. Machine learning algorithms generate highly personalized prosthetic designs and simulate bite dynamics to ensure natural integration with the patient's existing dentition[80]. For implant-supported restorations, AI assists in designing custom abutments and crowns that align precisely with implants and surrounding tissues[81].

AI applications include removable and complex prosthetics, biomechanical analysis, and automated manufacturing. In removable and full-arch restorations, AI-driven generative design ensures optimal strength, comfort, and aesthetics while allowing virtual treatment visualization. Biomechanical simulations predict stress distribution and implant stability, reducing complications and improving long-term success. Integrated manufacturing systems employ robotic milling and surface measurement for automated quality assurance, achieving micrometer-level precision. Although clinical studies have shown that AI enhances efficiency and accuracy, slight differences remain compared with expert human designs, indicating ongoing refinement toward full clinical parity[78,82].

7. Predictive Modeling for Implant Success and Complications

Machine learning models have been developed to predict implant survival, osseointegration success, and complication risk by integrating patient-specific factors, including demographics, medical history, bone quality, implant characteristics, and surgical variables[83]. For peri-implant disease detection. Machine learning approaches, including random forest, support vector machine, and neural network models, can predict peri-implantitis onset with accuracies ranging from 0.70--1.00, depending on the algorithm and outcome definition. However, systematic reviews note that most prediction models have limited external validation and methodological quality concerns, indicating the need for more rigorous development and testing[22].

8. Clinical Implementation and Workflow Efficiency

The real-world clinical deployment of AI systems in implant dentistry has demonstrated measurable benefits in workflow efficiency and diagnostic consistency. AI-powered CBCT interpretation reduces the average assessment time by 1.19 minutes (6.78%) per scan through automated dental charting and pathology detection. These time savings, while seemingly modest per case, accumulate significantly across high-volume practices. Moreover, AI systems facilitate standardized documentation and reduce interobserver variability, addressing a persistent challenge in radiological interpretation[84]. Studies examining clinician acceptance have revealed that dental professionals prefer AI to function as an augmentative tool complementing human expertise rather than as an autonomous decision-maker. The key facilitators of AI adoption include high diagnostic accuracy, real-time processing speed, and compatibility with existing digital workflows[85,86].

9. Current Limitations and Challenges

Despite promising accuracy metrics, several limitations constrain widespread AI adoption in implant planning. Data heterogeneity across CBCT devices, imaging protocols, and patient populations limits model generalizability. Many AI models are trained on datasets from single institutions or specific equipment, resulting in reduced performance when applied to external data sources. The scarcity of large, diverse, annotated datasets remains a fundamental bottleneck, particularly for less common anatomical variations and pathologies[87,88].

Technical limitations include challenges with cross-sectional bone measurements[89], interference from metal artifacts[28], and the detection of subtle anatomical variations[39]. The "black box" nature of deep learning models raises concerns about interpretability and clinical trust, particularly when diagnostic errors could have serious consequences. Additionally, there is a 17% miss rate and 2.8% false positive rate in certain applications, such as stent marker localization, indicating room for improvement[90,91].

Ethical considerations include data privacy, algorithmic bias, accountability for AI-generated errors, and potential exacerbation of healthcare disparities if training datasets lack demographic diversity. Regulatory frameworks often lag behind technological innovation, creating uncertainty around approval processes and liability. Furthermore, most published studies demonstrate high or unclear risk of bias due to methodological limitations, and only a minority have undergone external validation[92–95]. AI integration into clinical workflows faces significant logistical challenges. High costs, infrastructure requirements, and training needs remain prohibitive for smaller practices[96].

10. Future Directions and Emerging Technologies

The future of AI in implant planning will likely involve substantial progress in implant materials and digital technologies alongside persistent barriers to clinical translation. Smart implants with piezoelectric biosensors enable real-time monitoring when coupled with artificial intelligence, although standardization remains lacking[97]. FEMs in personalized dentistry have the potential to significantly improve treatment precision and efficacy, optimize outcomes and reduce complications. Their integration underscores the need for interdisciplinary collaboration and advancements in computational techniques to enhance personalized dental care[98].

Explainable AI (XAI) frameworks that provide transparent reasoning for algorithmic decisions are critical for building clinician trust and facilitating clinical adoption. Augmented reality applications for surgical visualization and hybrid AI models that combine multiple architectural approaches represent additional frontiers. The convergence of AI with 3D printing, photogrammetry, and light-field imaging may further refine accuracy and expand capabilities[99].

11. Conclusion

AI has demonstrated remarkable capabilities across the implant planning workflow, from anatomical segmentation and bone quality assessment to surgical guidance and outcome prediction. Current evidence supports AI's role as a clinical decision support system that enhances diagnostic accuracy, improves workflow efficiency, and augments, rather than replacing clinician expertise. While challenges related to data quality, model generalizability, algorithmic transparency, and ethical implementation persist, ongoing technological advances and interdisciplinary collaboration are progressively addressing these barriers. As AI systems mature and become integrated into routine clinical practice, they hold substantial promise for advancing precision, personalization, and predictability in dental implantology, ultimately improving patient outcomes and expanding access to high-quality implant care.

12. Declarations

Acknowledgments
Not applicable.

Ethical consideration
This study adhered to the principles of the Declaration of Helsinki.

Consent to participate
Not applicable

Conflicts of interest
Not applicable.

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Data Availability
The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Author(s) Contribution
Eslam Abdelwahab Dawood: Conceptualization, Methodology, Resources, Data Curation, Visualization, Investigation, Writing – original draft, **Bahaaeldeen M. Elgarba:** Formal analysis, Visualization, Investigation, review & editing, **Rocharles Cavalcante Fontenele:** Visualization, Investigation, review & editing, **Reinhilde Jacobs:** Conceptualization, Methodology, Supervision, Writing – review & editing

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