ISSN: 2582-6751
Journal of Clinical Medical Research

ATHENAEUM SCIENTIFIC PUBLISHERS

Review Article

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Grafting the Future: Implementing Artificial Intelligence in Guided Bone Regeneration

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Citation: Wiedemann TG. Grafting the Future: Implementing Artificial Intelligence in Guided Bone Regeneration. Jour Clin Med Res. 2026;7(2):1-5.

https://doi.org/10.46889/JCMR.2026.7214

Received Date: 14-07-2026

Accepted Date: 27-07-2026

Published Date: 04-08-2026

Abstract

Insufficient alveolar bone volume affects roughly one-third to one-half of patients presenting for implant therapy, making bone grafting and augmentation planning a central and technically demanding part of implant dentistry. This narrative review examines how Artificial Intelligence (AI) is being applied to plan, execute and monitor bone grafting procedures in implantology. Deep learning models now automatically segment the maxillary sinus, alveolar ridge and grafted bone volume on Cone-Beam Computed Tomography (CBCT) with accuracy approaching that of experienced clinicians while cutting analysis time more than twenty-fold. Machine learning classifiers assist in selecting graft materials and augmentation techniques, predicting postoperative bone gain and resorption and identifying anatomical risk factors such as sinus septa, mucosal thickening and cystic lesions before surgery. AI-guided design of three-dimensional printed scaffolds is further enabling patient-specific, defect-matched grafts with optimized porosity and mechanical properties. Despite this progress, heterogeneous datasets, limited external validation and the absence of prospective outcome trials currently constrain clinical translation. AI is best positioned today as a decision-support and workflow-efficiency tool that augments, rather than replaces, the surgeon's judgment in bone graft treatment planning.

Keywords: Artificial Intelligence; Bone Grafting; Dental Implants; Deep Learning

Introduction

Adequate bone volume and quality are prerequisites for predictable dental implant placement, yet periodontitis, post-extraction ridge resorption and maxillary sinus pneumatization commonly leave patients with insufficient alveolar bone [1,2]. An estimated 33 to 54% of patients requiring implants in the posterior maxilla need some form of sinus augmentation or ridge grafting before or during implant surgery [2]. Treatment planning for bone grafting has traditionally relied on two-dimensional radiographs and the clinician's manual interpretation of CBCT slices to estimate bone height, width and density, a process that is time-consuming and subject to inter-observer variability [3,4].

The growing availability of large CBCT datasets and advances in Convolutional Neural Networks (CNNs) have created an opportunity to automate and standardize bone graft planning. This review addresses three questions: (i) how AI supports pre-surgical assessment and planning of bone augmentation procedures; (ii) how machine learning contributes to graft material selection, scaffold design and prediction of graft outcomes; and (iii) what evidence exists on the postoperative monitoring of grafted bone using AI-based image analysis. The methodology, findings and clinical implications are presented in the following sections.

Materials and Methods

This article is a narrative literature review; no protocol was registered and no formal systematic methodology was applied. A literature search was performed in PubMed/MEDLINE, Scopus, Web of Science and Google Scholar for articles published between January 2019 and January 2026, combining the terms "artificial intelligence," "machine learning," "deep learning," "bone graft*," "bone augmentation," "sinus lift," "sinus augmentation," "guided bone regeneration," "3D printed scaffold," and "dental implant*." Reference lists of relevant systematic and scoping reviews were hand-searched to identify additional primary studies.

Eligible sources included peer-reviewed original research, systematic and scoping reviews and narrative reviews addressing AI or machine learning applications in any stage of bone graft planning, execution or monitoring within implant dentistry, as well as studies on AI-guided biomaterial and scaffold design relevant to alveolar bone regeneration. Conference abstracts without full text, non-English publications and studies unrelated to oral or maxillofacial bone grafting were excluded. Findings were extracted and organized thematically into pre-surgical assessment and planning, graft material selection and outcome prediction, scaffold design and postoperative monitoring; this structure forms the basis of the Results section below.

Results

AI-Assisted Pre-Surgical Assessment and Planning

The AI applications identified in this review map onto four interconnected stages of the bone grafting workflow - pre-surgical assessment, material selection and outcome prediction, scaffold design and postoperative monitoring - summarized schematically in Fig. 1.

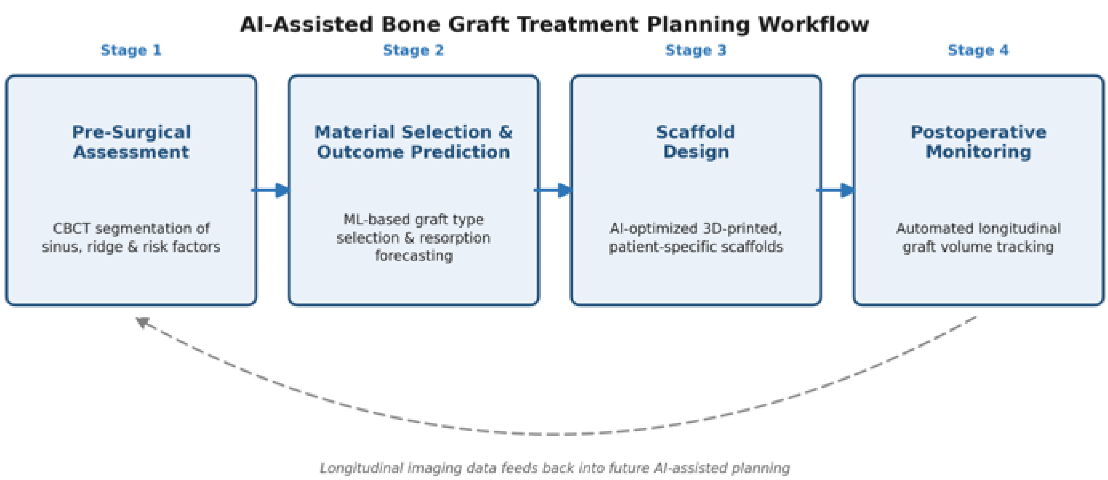

Figure 1: AI-assisted workflow for bone graft treatment planning in implant dentistry, spanning pre-surgical assessment, material selection and outcome prediction, scaffold design and postoperative monitoring.

The most extensively validated AI application in this area is automated segmentation of anatomical structures relevant to grafting. Deep learning models trained on CBCT scans can identify the maxillary sinus floor, posterior superior alveolar artery and alveolar ridge with sub-millimetric precision; one CNN model achieved Euclidean distance errors of 0.50 ± 0.31 mm and 0.38 ± 0.24 mm for two key alveolar ridge landmarks used to plan the lateral bony window in sinus lift surgery, summarized in Fig. 2 [3]. Other models automatically detect and classify maxillary sinus variations, including septa, mucosal thickening and cystic lesions, which are known risk factors for sinus membrane perforation and graft failure if unrecognized preoperatively [5-7].

Machine learning classifiers have also been developed to predict maxillary sinus cysts and their clustering patterns from patient and radiographic variables, supporting earlier identification of cases requiring modified surgical approaches [6]. Collectively, these tools reduce reliance on manual slice-by-slice CBCT review and standardize the identification of anatomical risk factors before graft planning begins [3,5,6].

Graft Material Selection and Outcome Prediction

Beyond anatomical assessment, AI models are being applied to graft material selection and the prediction of postoperative outcomes. A deep-learning-based automated system for maxillary sinus segmentation and bone graft analysis on CBCT demonstrated excellent agreement with manual measurements of bone graft volume (intraclass correlation coefficient = 0.993) while improving workflow efficiency more than twenty-fold, as summarized in Fig. 2 [4]. This system's predictable bias characteristics have been proposed as a basis for standardized prediction models of resorption patterns across different graft materials, including autogenous, allogeneic, xenogeneic and synthetic bone, potentially supporting more personalized, evidence-based selection of grafting material [4].

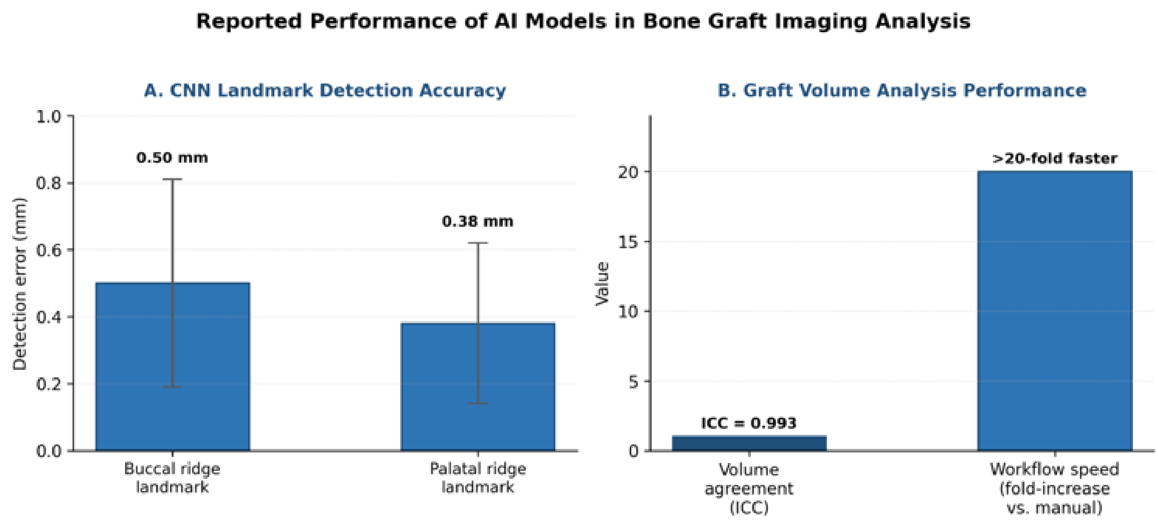

Figure 2: Reported accuracy of AI models in bone graft imaging analysis. (A) Mean detection error for CBCT alveolar ridge landmarks used in sinus-lift planning ± SD [3]; (B) Volumetric agreement between AI and manual bone graft measurements (ICC) and workflow speed gain of automated versus manual analysis [4].

Machine learning has additionally been used to identify differential predictors of early bone outcomes after transalveolar sinus floor elevation, analyzing variables such as endosinus bone gain, apical bone level and osteogenesis bone density derived from postoperative imaging [9]. These analyses suggest that bone quantity gained after grafting is more readily predictable from surgical parameters than bone quality or marginal stability, indicating that separate assessment strategies may be required for each outcome domain [9].

AI-Guided Scaffold Design and 3D-Printed Grafts

AI is also informing the design of patient-specific bone graft scaffolds intended for guided bone regeneration. Machine-learning-guided three-dimensional bioprinting has been used to optimize scaffold formulations, for example determining the optimal concentration of decellularized bone matrix in a gelatin methacrylate hydrogel scaffold to maximize printing fidelity while preserving bioactive signaling molecules for osteogenic differentiation [8]. Separately, machine learning approaches have been applied to predict the mechanical properties of scaffolds with diverse lattice structures, allowing scaffold porosity and geometry to be tuned computationally before fabrication rather than through iterative physical trial and error [11].

These AI-guided design approaches align with the broader concept of scaffold-guided bone regeneration, in which a slowly degrading, mechanically supportive scaffold is combined with graft material to reduce resorption and improve functional bone remodeling [12]. While most of the underlying evidence for AI-optimized scaffolds currently derives from preclinical and animal studies rather than human alveolar bone trials, the computational optimization principles are directly transferable to craniofacial and dental applications [8,11,12].

Postoperative Monitoring of Grafted Bone

AI-based image analysis is increasingly applied after grafting to monitor volumetric stability over time. Automated segmentation of bone graft material following maxillary sinus augmentation has been shown to outperform manual segmentation by surgeons in evaluating postoperative outcomes and has been proposed as a component of AI-driven CBCT analysis pipelines for surgical decision-making and prediction of mucosal complications in patients with low residual bone height [7]. Longitudinal registration-subtraction methods applied to sequential CBCT scans allow objective, standardized tracking of bone graft volume changes across time points, including in one-stage implant placement cases, replacing subjective visual comparison with quantitative measurement [4].

Discussion

The evidence reviewed indicates that AI is currently most mature in the segmentation and quantification stages of bone graft planning, where deep learning models achieve accuracy close to expert clinicians while dramatically reducing analysis time (Fig. 2) [3,4]. This automation directly addresses a longstanding bottleneck in grafting workflows: manual CBCT interpretation is time-intensive and subject to variability between clinicians, particularly for complex anatomical variants such as sinus septa or cystic lesions [5-7].

Applications in graft material selection, outcome prediction and scaffold design are comparatively earlier-stage. Predictive models for bone gain and resorption show promise but have so far demonstrated better performance for quantitative outcomes, such as bone volume, than for qualitative outcomes, such as bone density or marginal stability, which remain harder to predict from available variables [9]. Similarly, AI-guided scaffold optimization has strong support from tissue-engineering and materials-science literature, but most validation remains preclinical and dedicated trials applying these methods to alveolar or peri-implant bone defects in humans are still limited [8,11,12].

Several limitations temper the clinical translation of these tools. Most models are trained and validated on single-center or regionally limited CBCT datasets, raising concerns about generalizability across scanner types, patient populations and graft material combinations [3,4]. Prospective, multicenter studies with standardized outcome definitions are largely absent and no AI system currently automates the full grafting decision - material choice, technique selection and timing of implant placement - without clinician oversight. As with other AI applications in implant dentistry, informed consent should clearly convey that AI outputs are decision-support estimates rather than definitive treatment plans and grafting decisions should continue to rest with the treating surgeon [6,10].

Looking forward, the most promising near-term developments include integration of automated segmentation directly into surgical planning software, expansion of predictive models to incorporate systemic patient factors alongside radiographic data and closer coupling between AI-optimized scaffold design and chairside or in-office 3D printing for truly patient-specific grafts [4,8,9]. As with other narrative reviews, this article is subject to selection bias in the sources discussed and does not provide a pooled quantitative synthesis; systematic reviews and prospective clinical trials are needed to establish the true magnitude of benefit AI provides in bone graft treatment planning.

Conclusion

AI is measurably improving the speed, consistency and objectivity of bone graft treatment planning in implant dentistry, from automated segmentation of grafting-relevant anatomy to prediction of graft volume stability and computational optimization of scaffold design. Current evidence supports AI as a decision-support and efficiency tool rather than an autonomous planner and further prospective validation will be required before AI-derived graft recommendations can be adopted as a routine, unsupervised part of clinical practice.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial or non-profit sectors.

Acknowledgement

The authors have no acknowledgments to declare.

Data Availability Statement
The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethical Statement
The project did not meet the definition of human subject research under the preview of the IRB according to federal regulations and therefore was exempt.

Informed Consent Statement
Informed consent was obtained from all participants included in the study.

Authors' Contributions
All authors contributed equally to this paper.

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