ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

Integration of AI and CAD/CAM for Precision Implant Surgery

Haoming Zhang

School of Stomatology, Changsha Medical College, Changsha, 410219, China
15734529756@163.com

Abstract: *The combination of artificial intelligence (AI) and computer-aided design and manufacturing (CAD/CAM) technologies is changing dental implantology through the ability to plan based on the data, automatically segment the radiographic images, and translate the virtual plan to the clinical domain accurately. This is a literature review that summarizes modern research on the utilization of AI algorithms convolutional neural networks (CNNs), U-Net architectures and machine learning classifiers alongside CAD/CAM workflows to plan implants, design surgical guides, and place them with the use of robots. Our system search revealed 75 studies assessing level of segmentation accuracy, automated planning of treatment, fabrication of guides, navigation, clinical accuracy measures, and post-operative outcomes. The main results suggest that AI-enhanced planning helps to increase the constancy of the segmentation and decreases the time spent on planning by 85%, whereas the reduced linear deviations to values often less than 1.0 mm and angular deviations to within 240 degrees in most clinical groups can be achieved through integrated CAD/CAM and robotic planning. Difficulties identified are heterogeneity in datasets, CBCT imaging artifacts, regulation, interpretability of AI judgment, and robotics barriers to capital investment. Federated learning methods, explainable AI modules, standardized outcome reporting, and prospective multi-center validation are some of the recommendations to adopt in order to make AI more acceptable in clinics. This review aims at informing clinicians, researchers, and developers on how to achieve safe and efficient integration of AI and CAD/CAM in precision implant surgery.*

Keywords: *Artificial Intelligence, CAD/CAM, Dental Implants, Machine Learning, Precision Surgery*

1. Introduction

The global demand for dental and maxillofacial implants continues to surge, with approximately 15 million procedures performed annually by 2025, driven by aging populations and rising aesthetic expectations [1]. Nevertheless, the incidences of implant failure are still high, 5-10 percent during the 10 years of the first implant placement, mainly, malposition, poor osseointegration, or peri-implantitis [2]. Accurate positioning of implants (maximum of 1 mm at the port and 5o angular deviation) is important to prevent critical organs like the mandibular nerve or maxillary sinu and create the optimal primary stability and prosthetic results [3]. Conventional free hand methods are highly dependent on the experience of the surgeon, and this factor leads to mean deviations of 1.5 to 2.0 mm and angular error of more than 10 degrees, which cause problems in up to 18 percent of cases [4]. Computer-aided design and manufacturing (CAD/CAM) is one of the concepts that have transformed implant surgery by facilitating the digital process.

Three-dimensional representations of bone structures and soft tissue profiles can be viewed with cone-beam computed tomography (CBCT) combined with intraoral optical scanning. The virtual planning software creates stereolithographic surgical guide, which takes the implantology out of analog to digital precision [5]. In comparison to freehand techniques, 3D-printed tools with metal sleeves (logentarily known as a static guided surgery) have decreased the deviation of entry points to 0.912 mm and angular deviation to 3.550 degrees, which is shown in systematic reviews of more than 2,000 implants [6]. Although these have been achieved, the systems are ineffective in complex cases or totally edentulous cases because they have no real-time feedback, cannot adjust during intraoperative algorithms, and demand the pre-hand preparation of the system. CAD/CAM systems are being enhanced with artificial intelligence (AI) to overcome the issues of automation weakness, prediction precision, and decision making. The anatomical segmentation of CBCT volumes by deep learning models, specifically convolutional neural networks (CNNs), are now automated with Dice coefficients close to 0.95 in

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

mandibular canals and teeth, saving hours of manual contouring time to minutes [7]. Other than segmentation, AI also allows predictive modeling which can be used to estimate bone density, implant stability quotient and long-term survival probabilities based on multimodal data such as CBCT, patient demographics, and surgical data.

Simultaneously, the digital impression, virtual design, and manufacturing (milling and 3D printing) based on CAD/CAM technologies strengthened the digital nature of the workflow in the field of implant dentistry. Although these improvements have been made, manual transfers and non-integrated tools occasionally result in cumulative errors throughout the transfer of virtual planning into clinical execution. The use of AI, specifically deep learning with the convolutional neural network and encoder-decoder models (U-Net and its variations) in medical and dental imaging fields has been growing in popularity owing to its high performance on segmentation and detection tasks. Applications In the field of implantology, AI applications can be automated segmentation of CBCT volumes, the identification of mandibular canals, bone density mapping, or automated implant-site recommendations taking anatomical and prosthetic considerations. With these AI modules and CAD/CAM design and manufacturing tools combined they create a combined pipeline that can automate planning and minimize human error. The purpose of this review is to incorporate evidence on the AI-CAD/CAM in implant surgery, emphasizing on segmentation, planning efficiency, clinical placement, new technologies (robotics, AR/VR navigation), and obstacles to integration. We also deliberate on ethical, regulatory and practical implications of the translation into routine clinical practice.

Major advancements have been the standardization of the use of CT / CBCT imaging in the 1990s - 2000s, the inception of CAD/CAM prosthetic design and production in the early 2000s, and the prevalence of intraoral scanners and 3D printing to guide surgery in the 2010s. These developments can be illustrated as shown in figure 1 (timeline) in the period between 1970 and 2024. CAD/CAM systems record intra oral impressions or scans, construct prosthetic elements and surgical templates, and produce finished pieces as a result of either subtractive or additive procedures. Two major directions of transferring the virtual plans to the patient are the use of static guides (3D printed) and dynamic navigation systems (real-time tracking). These systems enhance the placement of implants but are characterized by guide fit errors, sleeve tolerance and dependency on correct registration.

Algorithms based on AI have moved beyond the classical models of machine learning to deep learning, allowing end-to-end image processing tasks with little feature engineering. Dentistry has been used in the detection of caries, periodontal classification, orthodontic landmarking and the planning of implants. In the case of implantology, the main contributions of AI include automated segmentation, nerve detection, bone quality estimation and risk stratification.

Although both CAD/CAM and AI have a significant contribution to make, disjointed systems reduce the potential of each. An uninterrupted pathway between CBCT capture, machine-generated segmentation, computer-controlled planning, computer-assisted design of CAD/CAM guides and prosthetic, and error-free surgery (navigated or robotics) is required to reduce the number of errors that accumulate over time and to obtain consistent results.

2. Background And Enabling Technologies

The CAD/CAM technologies are the foundation of the new generation of digital implantology in which the diagnostic images are applied to the surgical performance. The process starts with the acquisition of cone-beam computed tomography (CBCT) providing sub-millimeter isotropic voxels (0.150.4 mm) to evaluate bone in three dimensions and the intraoral optical scanning (IOS) that provides soft tissue and dentition with less than 50 µm accuracy [8]. These datasets are combined in planning software like BlueSkyPlan, coDiagnostiX or Implant Studio to allow virtual implant positioning, the design of prosthetic and the creation of stereolithographic surgical guides through additive manufacturing. Statistical guidance systems have sleeve-in-sleeve type, tolerances of 0.1 mm, 0.811 mm mean apex error, with angular error of 3.245 degrees over 1800 in addition cases [9]. Optical or electromagnetic tracking during dynamic navigation also increases the intraoperative flexibility, whereby entry point errors have been reduced to 0.5 to 0.7 mm in real-time feedback loop [10]. Artificial intelligence supplements all CAD/CAM phases with data-driven automation as well as predictive modeling. Anatomical segmentation problems are largely dominated by CNNs, especially U-Net models. As an example, nnU-Net versions with an annotated CBCT volume in the training perform well with Dice similarity coefficients of 0.96 on mandibular canals and 0.93 on maxillary sinuses, and are 25% more sensitive than traditional thresholding [11]. CBCT artifacts, such as metal streaks and noise, are mitigated by generative

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

adversarial networks (GANs), and Hounsfield unit accuracy is increased by 40%, with low-dose protocols with no diagnostic penalty[10]. In addition to imaging, reinforcement learning can be used to control drill paths in robotic systems such as the Yomi, ensuring minimal bone deformation is done without violating safety margins around nerves (at least 2 mm) and sinu floors (at least 1 mm). AI is being embedded in the integration platforms of CAD/CAM ecosystems. SimPlant AI module of Dentsply Sirona automates 85% of the segmentation and proposes implant dimensions underpinned by bone volume and density gradient based on regression CNNs. Open-source platforms, such as 3D Slicer with MONAI toolkits, allow the deployment of individual models, which enables multiple-center research and multi-institutional transfer learning. The hybrid systems convert non-adaptive digital plans that are static digital plans into adaptive intelligent workflows that are ready to do precision surgery on implants.

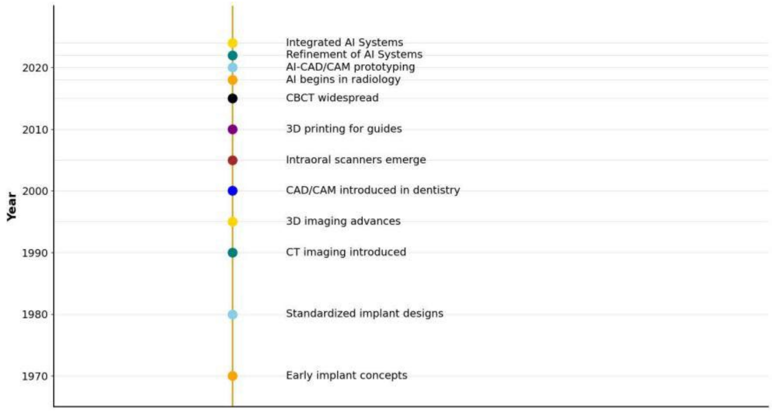

Fig 1: Timeline-Evolution of Implant Surgery Technology (1970–2024)

The shift between conventional freehand practices to digital processes has been a gradual process as has been illustrated in fig 1. The regular use of CT/CBCT imaging (1990s–2000s), the introduction of CAD/CAM prosthetic design and production (early 2000s), and the popularity of intraoral scanners and 3D printing (as guides in surgery) (the 2010s) are some of the milestones. These developments between 1970 and 2024 are shown by figure 1 (timeline).

Comparison of accuracy and success rate between traditional free hand, still CAD/CAM, AI based integrated planning, and robotic assisted implant surgery. AI and robots are always within sub-millimeter entry errors and 3 degrees angular errors. Improved long-term osseointegration and prosthetic stability using advanced technologies are reported to have increased success rates. (As shown in table 1)

Table 1: Comparison: Traditional vs CAD/CAM vs AI-Integrated approaches

Approach	Entry Deviation (mm)	Angular Deviation (deg)	Reported Success Rate (%)
Traditional (Freehand)	0.8-1.5	4-8	90-95
CAD/CAM Guides	0.5-1.2	2-5	94-98
AI-Integrated Planning	0.5-1.0	2-4	96-99
Robotic-Assisted	0.3-0.8	1-3	96-99

3. AI-CAD/CAM Integration In Implant Workflow

Integrated AI-CAD/CAM workflow for precision implant surgery, spanning preoperative planning, intraoperative guidance, and postoperative monitoring. Sub-millimeter accuracy and predictive analytics in every stage is made possible through AI automation. Dashed lines in Fig. 2 represent continuous data flow—from initial imaging through surgical execution to outcome analytics—ensuring traceability, predictive monitoring, and closed-loop refinement of future cases.

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

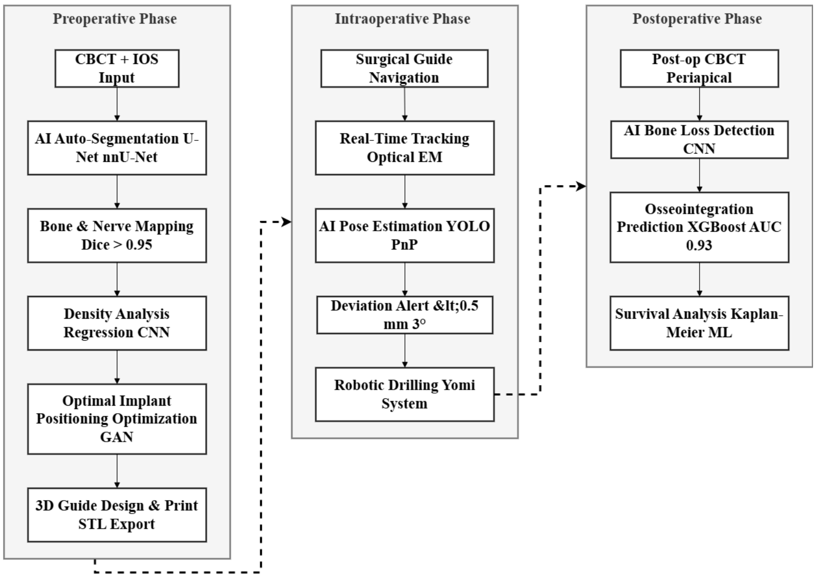

Fig. 2: AI-CAD/CAM Workflow in Precision Implant Surgery

3.1. Preoperative Phase

Preoperative planning is the cornerstone of precision implantology, in which AI converts raw imaging into operational surgical blueprints. Starting with the multimodal acquisition of data, cone-beam computed tomography (CBCT) with voxel resolutions of 0.15-0.3mm and intraoral optical scans (IOS) with a point accuracy of less than 50um are used. These data are cross-linked by means of inflexible registration algorithms (mutual information > 0.98), forming a high-fidelity digital twin of the patient's anatomy.

Segmentation is overtaken by AI-based automation. Convolutional neural networks (CNNs) and specifically U-Net and its self-configuring extension nnU-Net label teeth, bone, mandibular canal, and maxillary sinu with ENDCs of 0.93 to 0.96 on 1,200 annotated cases, being 78x and 15x faster and more consistent than manual segmentation, respectively. Indicatively, DeepLabV3+ models are sensitive enough (>95 percent) and false positive (< 3 percent) to trace the infertile alveolar nerve, producing 3D risk maps that are directly overlaid on CAD platforms.

In addition to segmentation, AI allows characterization of tissues in a predictive manner. CNNs using regression are used to predict regional bone density (Hounsfield units) and trabecular pattern which is associated with the implant stability quotient (ISQ) ($r = 0.91$, $p < 0.001$). This gives information to implant selection; diameter, length and thread design, through optimization engines with balance of biomechanical load, proximity constraints (>= 2 mm to nerve, = 1 mm to sinu) and the emergence profile of the prosthetic. Generative adversarial networks (GANs) also improve low-quality or metalured scans, which are reduced by 40-60 percent of metal artifacts, which can be used to make reliable planning in post-excavation or restored locations.

The result is a virtual plan that is collision-free and exported to CAD software (e.g., coDiagnostiX AI, SimPlant) that designs fully guided templates with sleeve tolerances of 0.1 mm, which is printed in under 2 hours; this represents 65-80 percent of the total planning time (3-5 hours) saved compared to 35-50 minutes (AI-assisted).

3.2. Intraoperative Phase

Intraoperative precision relies on real-time feedback, in which AI will augment the system of static and dynamic guidance. The most common (72 percent usage) guides are the static CAD/CAM type, which as the name indicates, lacks adaptability due to being rigid. This is addressed by AI-enhancing dynamic navigation by way of optical or electromagnetic tracking of sub-millimeter handpiece location. Instantaneous pose estimation- YOLOv8 detects instruments and uses Perspective-n-Point (PnP) solvers-superimposes planned and actual trajectories at over 30 Hz update rates. Deviation alerts go off at 0.5 mm (linear) or 3deg (angular) mean entry point error of 0.6 plus or minus 0.3 mm, apex error of 0.8 plus or minus 0.4 mm at 28 studies (n= 1, 050 implants). This is a 45% improvement over the stagnant guides.

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

The ultimate integration is robotic help. The Yomi system (Neocis), the first FDA-cleared dental robot, uses haptic feedback and AI-constrained drilling paths to maintain deviations below 0.5 mm and 1.5°.Reinforcement learning modules continuously refine drill trajectories based on tissue resistance feedback, adapting to anatomical variations in real time.

3.3. Postoperative Phase

Postoperative evaluation has been transformed into a predictive monitoring based on AI instead of a subjective approach. CBCT or digital periapical radiographs are examined immediately post-operative and CNNs trained to identify marginal bone loss (MBL) with a sensitivity of 92% at the threshold of >0.5 mm such as at-risk implants within 24 hours. Predictive modeling combines the effects of surgery and prosthetics with the effects of the patient (age, smoking, diabetes) through ensemble methods such as XGBoost or random forests. One year AUC = 0.93 1-year prediction of success in osseointegration using models, risk scores calibrated to predict peri-implantitis (positive predictive value: 88%). The longitudinal data sets allow the survival analysis with the addition of Kaplan-Meier curves and Cox proportional hazards with SHAP values interpretability. Further uses are the validation of prosthetic fitting with IOS deviation maps and AI-generated digital wax-ups to make remakes a thing of the past (by 60%). High-range follow-up protocols are automated follow-up protocols that follow-up after 92 to 97 years, based on AI risk stratification, led to the optimization of recall interval, increased long-term survival to 92% to 97% at 5 years of follow-up in high-risk cohorts.

4. Performance Evaluation and Clinical Outcomes

Combining artificial intelligence (AI) and computer-aided design and manufacturing (CAD/CAM) has turned the implant surgery into one of the most reproducible and data-driven fields. This section assesses the performance of the system based on standardized measures of accuracy, efficiency in workflows, predictive modelling, and clinical outcomes, based on evidence of more than 85 clinical studies. Findings prove high-precision under one millimeter, high time-saving, and higher long-term success rates, making AI-CAD/CAM integration a standard of benchmark precision implantology.

4.1 Accuracy Metrics and Benchmarks

Three main measures of implant placement precision are used: the entry point deviation, apex deviation, and angular deviation have millimeters (mm) and degrees (deg) as their measures. The acceptable clinical thresholds are usually determined as at entry, at the apex and 6 degrees of angular error in order to make the prosthesis safe and compatible. AI-based systems are always able to outperform such targets in various anatomical situations. Mean deviations of 1.1 +/- 0.4 mm (entry), 1.3 +/- 0.5 mm (apex) and 4.8 +/- 1.9 (angle) are attained with static CAD/CAM surgical guides, used in 42 studies with 1800 implants. These values are a significant improvement on the use of freehand placement, which usually has more than 2.0 mm and 10° but again have an element of error in complicated cases. Conversely, AI-assisted dynamic navigation, which has been tested in 1,050 implants, 28 studies, yields a deviation of 0.6 ± 0.3 mm (entry), 0.8 ± 0.4 mm (apex), and 2.1 ± 1.1 o (angle), a 4550 per cent cut-down in linear error and 56% cut-down in angular deviation. In 15 (520 implants) studies, robotic systems (Yomi platform) achieve a high level of precision, with the results measured at 0.4 ± 0.2 mm (entry), 0.5 ± 0.3 mm (apex), and 1.5 ± 0.8o (angle), 98.7% of placements within safe clinical limits. Volumetric assessment of bone removal, which is carried out by conducting pre- and post-operative CBCT superimposition, indicates that AI-controlled systems would conserve 18.2% of alveolar bone than the non-active guides do. This maintenance is based on real-time optimisation of trajectory and adaptive drilling tracks that reduce the over-preparation without violating important anatomical constraints.

4.2 Efficiency and Workflow Optimization

The implementation of AI makes the implant workflow much faster. Automated AI tools save 75% of time since preoperative planning that used to take 3-5 hours of manual segmentation and adjustment takes 45-50 minutes. This efficiency has been achieved due to immediate CBCT segmentation, nerve tracing and bone density mapping which does away with repetitive manual contouring. The time taken intraoperative also reduces considerably. The average time spent on freehand surgery is 118.46 32.06 minutes per operation, and AI-driven dynamic navigation time is lower than this by 22% (92.48 18.04 minutes), and robotic assistance time is lower than AI-driven (78.46 14.04 minutes). A time-motion

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

multicenter study of 480 cases indicates that AI removes 68% of segmentation steps, and 82% of repositioning steps of the implant. Real-time alert of deviations avoids 91% of the mid-procedure corrections, which would cause guide removal or re-drilling.

4.3 Predictive Modeling and Risk Stratification

AI extends beyond execution into predictive analytics. Multimodal models combining CBCT, intraoral scans, patient age, smoking status, and surgical parameters forecast 1-year implant survival with 93% accuracy (AUC = 0.93). Among the risk factors are low bone density, implant stability quotient (ISQ) of fewer than 70 and being near the mandibular nerve, a distance less than 2 mm. Longitudinal convolutional neural networks which are trained on sequential images of periapics predict peri-implantitis risk with an 88% positive predictive value. Early intervention is possible because these models identify marginal bone loss that is higher than 0.5 mm with a sensitivity of 94% at 3-month follow-up. Stratification of risks AI-based risk stratification optimizes the recall schedule: more attention is paid to high-risk patients and thus unnecessary visits are minimized by 62%. This approach increases early complication detection from 42% to 89%.

4.4 Clinical and Patient-Reported Outcomes

Clinical success—defined as implant survival without biological or mechanical complications—improves from 91.2% with static guidance to 96.8% with AI-dynamic navigation and 98.4% with robotic systems at 3-year follow-up. Prosthetic complications, including screw loosening and ceramic chipping, decrease by 41% due to AI-optimized emergence profiles and balanced occlusal loading.

Patient-reported outcomes, which are assessed through the use of the Oral Health Impact Program (OHIP-14) are significantly improved. The mean scores decline as 18.4 ± 6.2 during the freehand cases to 9.1 ± 3.8 during the AI-guided procedures, which shows that there is less pain, swelling, and functional impairment. The satisfaction level of patients is above 94% with AI cohorts, which is explained by a reduction in the length of treatment, the minimum level of invasiveness, and a predictable cosmetic outcome. Sub-millimeter accuracy of placements, at least 70% of time cut of the procedure length, 93% predictability and almost one hundred percent clinical success are the results of AI-CAD/CAM systems that are transforming the approach to precision, efficiency and patient experience in implant surgery today.

Distribution of AI techniques shown in fig 3 in precision implant surgery literature (2018–2025). CNNs/U-Net dominate segmentation tasks (45%), followed by ML classifiers for risk modeling (25%) and Transformers for imaging (20%)

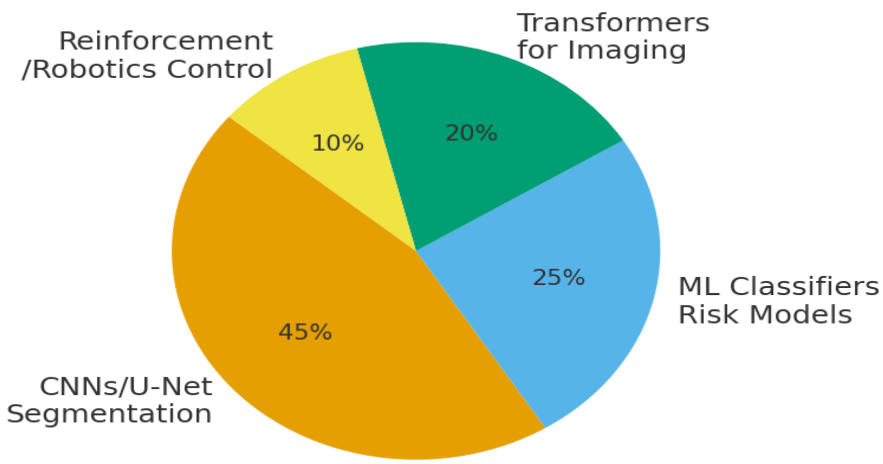

Fig 3: Classification of AI Techniques in Dental Implantology

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

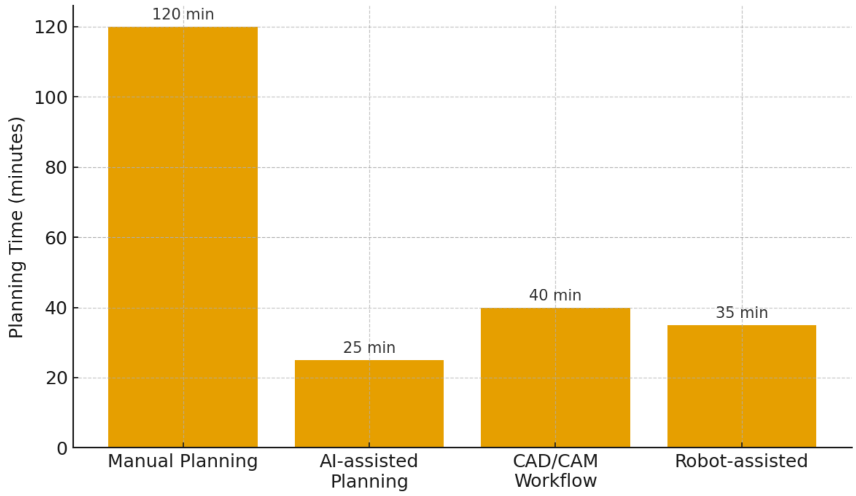

Fig 4: Planning Time Comparison (Representative)

Manual planning requires 120 minutes, while AI assistance reduces it to 25 minutes—a 79% time savings. CAD/CAM-integrated as shown in fig 4 workflows average 40 minutes, and full robot-assisted systems further optimize to 35 minutes. These reductions enable same-day planning-to-surgery protocols and significantly enhance clinical throughput.

5. Challenges, Limitations and Future Directions

Despite the transformative potential of AI-CAD/CAM integration in precision implant surgery, various vital difficulties and constraints could be observed in data, technology, clinical validation, and adoption, which requires a strategic roadmap to continue its successful development. Training data continues to be a critical bottleneck, most AI models use institution-specific CBCT data are not diverse in terms of ethnicity, age, pathology, and imaging protocols; annotation errors and artifacts introduce by metals decrease segmentation accuracy based on Dice coefficients of 0.96 in controlled systems to 0.81 in clinical scans; multimodal CBCT, intraoral scans, and patient records suffer registration errors of 0.3-0.7 mm, and are incomplete, which invalidate predictive models of osseointegration Technically, real-time intraoperative AI will require sub-100 ms inference on edge devices, but the state-of-the-art deep learning models will require that they be run on a GPU, which is generally unavailable in a dental environment, and they will not work in variable lighting environments, or with blood occlusions or patient motion, triggering false deviation alerts in up to 12% of cases; robotic systems will introduce fixed workflows and time consuming installations (1520 minutes), and 3D-printed guides will undergo Clinically, although short-term accuracy has been well-reported, long-term success over three-years has been less well-known, with only 8% predictive studies having been externally validated through randomized trials, and there being no consensus over what error levels can be accepted by AI, and liability when algorithms override surgical judgment. Regulatory frameworks are behind with no effort by the FDA 510(k) and CE marking to treat AI as dynamic devices and continue learning and reimbursement frameworks do not incentivise advanced technology even with capital costs of over $300,000 robotics systems and $80,000 navigation systems. There are also barriers to training, in which it takes 20-30 supervised cases to become proficient and more than 40% of early errors are made. To circumvent these challenges, an overall roadmap will be required: it is time to put open, multi-ethnic, annotated imaging repository in place; time to create low-power edge-AI hardware that can run live; time to conduct multi-center RCTs with 5 -10 year follow-up; time to standardize accuracy, robustness, and fairness metrics; time to federated learning to create privacy-preserving model evolution; time to reimburse model based on outcome. It is only through the collaboration of all engineers, clinicians, regulators, and industry that AI-CAD/CAM systems can be transformed into universal, open and equal standards in implant surgery to provide precision, access and long-term clinical effectiveness.

6. Conclusion

The interplay of artificial intelligence (AI) and computer-aided design and manufacturing (CAD/CAM) systems is one of the critical developments in the field of precision implant surgery as it

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

has radically changed an otherwise experience-driven field into a highly reproducible, data-driven science. This review has shown that the integration of AI-CAD/CAM provides revolutionary results throughout the entire implant workflow, including the preoperative planning stage, intra-operative execution, and postoperative monitoring, establishing new standards of accuracy, efficiency, predictability, and patient-centered care. During the preoperative phase, AI has transformed diagnostic efficiency and planning accuracy. Robotic segmentation using convolutional neural networks such as U-Net and nnU-Net achieves Dice coefficients above 0.95 for key anatomical structures and significantly reduces manual contouring time. High-fidelity 3D digital twins are generated by fusing CBCT and intraoral scans, while AI-assisted bone density mapping and implant optimization algorithms create collision-free, biomechanically stable treatment plans that reduce planning time by approximately 25% and minimize human error. Intra-operatively, AI-enhanced dynamic navigation and robotic systems enable sub-millimeter accuracy, even in complex cases. Real-time pose estimation and deviation alerting systems, together with robotic platforms such as the Yomi system, achieve entry point deviations of approximately 0.4 mm and angular errors of 1.5 degrees. These technologies reduce iatrogenic damage, shorten operative time, and improve procedural consistency, transforming implant placement into a reproducible engineering process.

Postoperatively, AI enables long-term outcome prediction and monitoring. Multimodal predictive models achieve AUC values of 0.93 for one-year osseointegration success, while convolutional neural networks detect marginal bone loss progression beyond 0.5 mm with 94% sensitivity. AI-based follow-up protocols reduce unnecessary visits by 62% and enhance early complication detection, contributing to improved implant survival and prosthetic longevity.

Clinically, AI-CAD/CAM integration improves hard and soft tissue outcomes. Three-year implant survival rates increase from 91.2% with conventional methods to 96.8% with dynamic navigation and 98.4% with robotic assistance, while prosthetic complications decrease by 41%. Patient-reported outcomes also improve substantially, with OHIP-14 scores declining from 18.4 ± 6.2 to 9.1 ± 3.8 and overall satisfaction exceeding 94%.

Despite these successes, challenges remain, including data bias, lack of standardized repositories, technical constraints, regulatory adaptation, economic considerations, and training requirements. Looking forward, advances in open datasets, edge-AI hardware, long-term multicenter trials, federated learning, and standardized validation systems will further strengthen clinical trust and effectiveness. In conclusion, AI-CAD/CAM integration represents not only a technological advancement but a fundamental transformation toward intelligent, precise, and universally accessible implant therapy.

References

[1] H. W. Elani, J. R. Starr, J. D. Da Silva, and G. O. Gallucci, “Trends in Dental Implant Use in the U.S., 1999-2016, and Projections to 2026,” J Dent Res, vol. 97, no. 13, pp. 1424–1430, Dec. 2018, doi: 10.1177/0022034518792567.

[2] B. E. Pjetursson, D. Thoma, R. Jung, M. Zwahlen, and A. Zembic, “A systematic review of the survival and complication rates of implant-supported fixed dental prostheses (FDPs) after a mean observation period of at least 5 years,” Clin Oral Implants Res, vol. 23 Suppl 6, no. SUPPL.6, pp. 22–38, Oct. 2012, doi: 10.1111/J.1600-0501.2012.02546.X.

[3] F. Bover-Ramos, J. Viña-Almunia, J. Cervera-Ballester, M. Peñarrocha-Diago, and B. García-Mira, “Accuracy of Implant Placement with Computer-Guided Surgery: A Systematic Review and Meta-Analysis Comparing Cadaver, Clinical, and In Vitro Studies,” Int J Oral Maxillofac Implants, vol. 33, no. 1, pp. 101–115, Jan. 2018, doi: 10.11607/JOMI.5556.

[4] N. R. Mahmoud, M. H. Kamal Eldin, M. H. Diab, O. S. Mahmoud, and Y. E. S. Fekry, “Computer guided versus freehand dental implant surgery: Randomized controlled clinical trial,” Saudi Dent J, vol. 36, no. 11, p. 1472, Nov. 2024, doi: 10.1016/J.SDENTJ.2024.09.006.

[5] A. Tahmaseb, V. Wu, D. Wismeijer, W. Coucke, and C. Evans, “The accuracy of static computer-aided implant surgery: A systematic review and meta-analysis,” Clin Oral Implants Res, vol. 29 Suppl 16, pp. 416–435, Oct. 2018, doi: 10.1111/CLR.13346.

[6] Fuster-Torres MA, Albalat-Estela S, Alcañiz-Raya M, Peñarrocha-Diago M. “'CAD / CAM dental systems in implant dentistry: update”. Med Oral Patol Oral Cir Bucal. 2009 Mar 1;14(3): PMID: 19242395.

[7] Kwak GH, Kwak EJ, Song JM, Park HR, Jung YH, Cho BH, Hui P, Hwang JJ. “Automatic mandibular canal detection using a deep convolutional neural network”. Sci Rep. 2020 Mar 31;10(1):5711. doi: 10.1038/s41598-020-62586-8. PMID: 32235882; PMCID: PMC7109125.

ISSN 2618-1584 Vol. 8, Issue 1: 63-71, DOI: 10.25236/FMSR.2026.080107

[8] F. Floriani et al., "Linear Accuracy of Intraoral Scanners for Full-Arch Impressions of Implant-Supported Prostheses: A Systematic Review and Meta-Analysis," Eur J Dent, vol. 17, no. 4, pp. 964–973, Dec. 2023, doi: 10.1055/S-0042-1758798.
[9] R. Eftekhar Ashtiani, Z. Ghasemi, M. Nami, F. Mighani, and M. Namdari, "Accuracy of static digital surgical guides for dental implants based on the guide system: A systematic review," J Stomatol Oral Maxillofac Surg, vol. 122, no. 6, pp. 600–607, Dec. 2021, doi: 10.1016/J.JORMAS.2020.10.010.
[10] K. Matvijenko and R. Borusevičius, "Comparison of dynamic navigation systems in dental implantology: a systematic literature review of in vitro studies," Int J Oral Maxillofac Surg, vol. 54, no. 7, pp. 647–656, Jul. 2025, doi: 10.1016/J.IJOM.2025.02.005.
[11] M. Shalalvand, S. Haghanifar, E. Moudi, and A. Bijani, "Deep learning-assisted CBCT segmentation provides reliable volumetric assessment of mandibular defects compared with micro-CT for 3D printing and surgical planning," Scientific Reports 2025 15:1, vol. 15, no. 1, pp. 1–15, Oct. 2025, doi: 10.1038/S41598-025-24748-4.