Artificial Intelligence in Dental Implant Planning and Prosthodontic Rehabilitation: Current Advances, Challenges, and Future Directions

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***Abstract*—Over the years, dental implant treatment has improved significantly and artificial intelligence (AI) has become an important tool in this field. Now, AI is tasked with analysing dental images, studying CBCT scans, identifying implant systems, planning implant placement, and monitoring bone changes around implants. There are several AI techniques, such as convolutional neural networks (CNNs), U-Net, YOLO, Faster R-CNN, vision transformers and artificial neural networks (ANNs), that are being studied for these applications. In this paper, we summarize recent research carried out in the area of AI in dental implant planning and prosthodontic rehabilitation. It is evident that AI can improve accuracy, reduce planning time and assist clinicians while the expert dentist makes the treatment decisions. Such responsible use of AI further enhances precision of implant placement, reducing risk, optimising aesthetics and hence improving the overall success rates. However, there are several studies that are limited by small datasets and a lack of long-term clinical validation. Still, for now, AI is being considered as a supportive tool that helps clinicians rather than a technology that will replace professional judgment. Obviously, the future research should be carried out on larger datasets, better validation methods, and improved integration of AI into routine clinical practice to achieve significantly balanced studies and conclusive observations. Further, it is now established without doubt that AI bears the potential to become a valuable part of modern implant dentistry.**

***Index Terms*—Artificial intelligence, Cone-beam computed tomography, Deep learning, Dental implants, Marginal bone loss, Prosthodontic rehabilitation**

I. INTRODUCTION

Dental implants are used restore both function and appearance by replacing the missing teeth [1]. The success of the implant treatment depends on proper diagnosis, careful planning, adequate bone evaluation, and consideration of the final prosthetic restoration [2]. Dentists generally combine the use of panoramic radiographs, periapical radiographs, and cone-beam computed tomography (CBCT) scans to assess the implant site before treatment [2], [3].

While these imaging methods may provide valuable information, and help interpreting them better and sometimes inadequate too, especially in complex cases. Differences in experience among clinicians may also lead to variations in treatment planning [4]. Owing to these challenges, researchers have started exploring the use of artificial intelligence in implant dentistry specially during diagnosis and planning.

AI systems can analyze dental images and identify patterns with a high confidence score that may not always be obvious during routine examination [5]. Therefore, the use of AI can help improve efficiency and reduce the time required for treatment planning.

However, AI cannot be viewed as a replacement for clinical expertise. Instead, it should be considered an adjunct tool to augment the dentist's diagnosis and treatment planning [6]. Final decisions should also take into account the patient's medical history, clinical findings, treatment needs, esthetic expectations and financial implications.

II. SEARCH METHODOLOGY

This paper presents a narrative review of the current use of artificial intelligence in dental implant planning and prosthodontic rehabilitation. Relevant articles

were collected from PubMed, Cochrane Library, Web of Science, IEEE Xplore, OpenGrey and were supplemented with information obtained from Google Scholar and Scopus, and cross-references of the selected articles.

The review focuses on major areas where AI is being applied in implant dentistry, including CBCT analysis, implant planning, CNN, YOLO, implant system identification, bone assessment, marginal bone loss detection, digital workflows, and prosthodontic applications. Studies comparing AI performance with human clinicians in decision making were also included.

Inclusion criteria: Only original research papers, systematic reviews, meta-analysis, or narrative review articles that had been written in English and were selected if they examined the utilization of AI in dental implants planning, CBCT examination, virtual implant placement, implant detection and classification, bone examination, detection of marginal bone loss, digital workflow, and implant-supported prosthodontic rehabilitation. Papers in which machine learning, convolutional neural networks (CNNs), U-net, YOLO, Faster R-CNN, Mask R-CNN, vision transformers, or any other technique based on the application of AI to dental imaging had been studied were considered for inclusion.

Exclusion criteria: Papers published before 2020, or in a language other than English, were not included. Case reports, case series, letters, editorials, commentaries, conference abstracts and preprints that had not undergone peer review were also left out, as were duplicate publications and articles whose full text could not be obtained. Work on artificial intelligence in other branches of dentistry, such as caries detection, orthodontics or oral cancer screening, were considered only where it had a direct bearing on implant planning or implant-supported prosthodontic rehabilitation. Purely technical papers with no application to dental imaging were excluded along with the digital or CAD/CAM workflows in which no AI component was involved. Titles that were clearly unrelated to the topic were discarded at the first screening stage, and the abstracts were then read in detail to narrow the selection further. Finally, articles that gave insufficient methodological detail, or that reported no performance outcomes, were not carried forward.

III. INTRODUCTION TO AI

Artificial intelligence (AI) is the branch of computer science concerned with building machines that carry out work ordinarily requiring human judgement, and its use across healthcare is expanding rapidly. The field acquired its name at a summer workshop convened at Dartmouth College in 1956 by John McCarthy, together with Marvin Minsky, Nathaniel Rochester and Claude Shannon [7]–[9]. An AI system is one that can interpret an image, recognise speech, weigh competing alternatives and arrive at a decision, all tasks that would otherwise require a trained human observer [9]. Unlike conventional software, which follows rules written by a programmer, these systems learn from examples. The algorithm is shown a large number of radiographs in which the teeth, bone or implants have already been outlined by clinicians, and with every pass it corrects itself until its output comes close to what the experts marked [10]. Once this training is complete, the model is tried on scans it has never seen before, and the patterns it has picked up are then applied to new clinical cases. The families of method gathered under this heading, and the ones that matter for the present review, are machine learning (ML), convolutional neural networks (CNNs), encoder-decoder networks, artificial neural networks (ANNs) and robotics [9], [11].

Even though artificial intelligence has been studied within dentistry using artificial neural networks since the 1990s, its application within dental implantology has significantly multiplied in the last ten years [7]. The initial studies of AI in relation to dental implants mainly revolved around CBCT image segmentation and the localization of anatomic landmarks, whereas dedicated deep-learning systems related to dental implants have been described only in recent years [9].

A. Machine Learning with Structured Data

Machine learning uses computer algorithms that learn from existing data and make predictions based on patterns. In implant dentistry, these methods can be used to estimate the risk of implant failure by considering factors such as age, smoking habits, medical conditions, bone quality, and implant characteristics [12]–[14]. Machine learning adds the advantage my making the results often easier to understand compared to more complex AI models.

B. Convolutional Neural Networks (CNNs)

CNNs are some of the most commonly used AI models in medical and dental imaging [10]. They can automatically pick-up important features within an image and are widely used for detecting teeth, implants, caries, and other dental conditions [15], [16]. In implant dentistry, CNNs help analyze radiographs and identify structures that are important for treatment planning [17].

C. Encoder-Decoder Networks for Segmentation

Image segmentation refers to separating different anatomical structures within an image. U-Net is a popular AI model used for this purpose [18]. It can identify structures such as teeth, bone, mandibular canals, and maxillary sinuses on CBCT scans [17]. Accurate segmentation helps clinicians create digital treatment plans and surgical guides [12], [19].

D. Object Detection: YOLO and Faster Region-based CNN

YOLO is a fast object detection AI model used to detect and classify many objects at once. YOLO is fast, but Faster R-CNN is more detailed. YOLO identifies and classifies the image by dividing it into a grid [20]. Each cell in the grid predicts if there is an object in that location and what type. YOLO then draws a box around each object that it detects and assigns a label such as tooth or implant [16], [21]. The box helps YOLO determine location of the detected object by its center coordinates, width and height [21]. Faster R-CNN is an AI model designed to locate areas that may contain an object and then it identifies objects within images with higher accuracy [21]. Faster R-CNN first uses a Region Proposal Network (RPN) to detect regions in the image. These images are then analyzed very closely by Convolutional Neural Networks (CNN). Here, CNN helps YOLO refine its bounding box [16]. This helps locate the object more accurately.

E. Mask R-CNN and Instance Segmentation

Mask R-CNN is an advanced version of object detection technology. It can identify structures as well as outline their exact shape [22]. This is useful when multiple teeth or implants are located close together and need to be analyzed separately [23].

F. Vision Transformers and Multimodal Models

Vision transformers are newer AI models that focus on understanding the overall image rather than just small areas [24]. They may be useful in future dental applications because they can combine information from CBCT scans, intraoral scans, photographs, and patient records. However, they require large amounts of data and are still being studied in dentistry. Multimodal artificial models combine information from multiple data sources such as dental radiographs, intraoral scans, clinical photographs to improve diagnosis and treatment planning.

G. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are AI algorithms that try to replicate the process of learning done by the human brain using massive data sets [7]. In implant dentistry, these ANNs have been employed to determine the success of implants, analyze the risk of implant failure, and aid in treatment planning using clinical and radiographic information including bone density, implant information, and patient information [12], [13]. They are capable of performing well but require high quality data [25].

IV. AI APPLICATIONS IN DENTAL IMPLANTS

A. CBCT Analysis

CBCT imaging provides detailed three-dimensional information about the jaws and surrounding structures [26]. This information is essential for safe and accurate implant placement. AI is now being used to support several stages of CBCT analysis and treatment planning for dental implants. Lahoud et al. (2022) trained a deep learning tool on 235 CBCT scans to trace the mandibular canal automatically. The canal was outlined accurately and in significantly less time when compared with tracing, which is of paramount importance when planning implant placement in the posterior mandible [27]. Lin et al. (2023) reported similar findings using a two-stage 3D U-Net on 220 scans, with a mean Dice similarity coefficient of 0.875 for the same structure [28]. Taken together, these studies suggest that automated detection of the mandibular canal is reaching a level of reliability that is acceptable for routine planning [29].

B. Virtual Implant Placement

Virtual implant placement is an advanced digital treatment planning technique wherein the optimal implant location, implant angulations, and depth of the implant are assessed by means of three-dimensional images obtained from Cone Beam Computerized Tomography (CBCT) [30]. Using this procedure, dentists are able to assess bone availability and detect anatomical landmarks as well as plan implants according to the final prosthodontic results prior to the operation [19], [30]. With recent advancements in Artificial Intelligence (AI), virtual implant placement has been greatly enhanced through automated image segmentation, anatomical landmarks recognition, and implant positioning [19]. Deep learning approaches have demonstrated their efficacy in this regard, and a significant difference has been observed in U-net, CNNs, and vision transformers [18].

BM Elgarba et al. (2024) showed that AI-based automatic virtual implant positioning resulted in similar implant plans to those prepared by experienced professionals [30]. The model mostly applied U-NET, which is designed for image segmentation. Hendi KD et al. (2024) mentioned several uses of AI in the field of prosthodontics, such as digital treatment planning, prosthesis design, occlusal analysis, and computer-aided designing and manufacturing [25].

C. Edentulous Region Identification and Bone Measurement

Proper identification of the edentulous area and evaluation of the bone present are key to effective planning for implant placement [19]. There has been promising progress made in utilizing AI to automate these processes using the imaging provided by CBCT scans. Deep learning algorithms have been used to effectively identify the missing teeth area and the present alveolar bone. In addition, the available bone height and width can be estimated using the same approach [17].

According to Dawood et al. (2026) the AI-assisted implant planning system was 96% accurate in detecting edentulous area in the mandible while it was 83% accurate in the maxilla. These results indicate that AI is able to detect missing tooth areas and assist clinicians to measure the available bone for implant placement [19].

D. CBCT-to-Intraoral Scan Registration

The CBCT-to-intraoral scanning registration is a critical component of the digital implant planning process that allows integrating the three-dimensional anatomy available via CBCT images with the morphological information available through intraoral scanning devices. The possibility to combine the information regarding both hard and soft tissues allows developing prosthetically oriented treatment planning and manufacturing of precise surgical guides. The use of artificial intelligence (AI) in this procedure allowed simplifying and streamlining the process of the registration [31]. Various deep learning networks were proposed as tools for solving image registration tasks and extracting anatomical features including CNNs, U-Net, Point Net / Point Net++, and Vision Transformers. Hybrid deep learning models with the usage of CNNs and Transformers are actively being implemented for CBCT to intraoral scan registration.

Ntovas P et al. (2024) proved the efficiency and high level of accuracy of CBCT and intraoral scans artificial intelligence-based registration compared to manual registration techniques [31], [32]. However, expert evaluation is required to detect possible mistakes in the process of registration.

E. Radiographic Implant Identification

Radiographic implant identification entails the identification and classification of dental implants based on radiographic imaging modalities such as periapical imaging, panoramic imaging, and Cone Beam Computed Tomography (CBCT) imaging. Radiographic implant identification is critical in the absence of the patient's dental implant records since it facilitates treatment planning for implant maintenance and rehabilitations. Modern developments in the field of artificial intelligence (AI) have led to significant improvement in the identification of dental implants by virtue of implant imaging through machine learning [15]. The features covered by deep learning include the shape, threads, collar, apex, and internal connection of the dental implants [33].

Ibraheem et al. (2024) reviewed AI models for implant fixture identification and reported diagnostic accuracies ranging from 67% to 98.5%, with most studies exceeding 90% accuracy [15]. Features like implant shape, thread design, and collar characteristics can help in recognizing different implant systems and augment further treatment procedures. In particular,

deep learning models like Convolutional Neural Network (CNN) have been used to identify implant system brands accurately, whereas object detection and image segmentation models have played an important role in detecting and characterizing implants.

F. Marginal Bone Loss Detection

Marginal bone loss is a process of gradual resorption of the alveolar bone that surrounds the cervical portion of the dental implant post-surgery. This clinical parameter is significant in assessing the health status of the dental implants because excessive bone loss signifies peri-implantitis disease, instability of the implant or even its possible failure. As such, early identification of marginal bone loss is important for proper management of the condition.

Artificial intelligence has shown great promise in detecting and analyzing marginal bone loss based on periapical, panoramic radiographs, and cone-beam computed tomography images [34]. Deep learning algorithms and models, especially the convolutional neural networks (CNN) and the U-Net segmentation network, can successfully distinguish the implant platform, detect crestal bone level and measure the change in marginal bone height [35].

Li Y et al. (2025) have shown high sensitivity and specificity of AI-based methods for predicting marginal bone loss in patients with dental implants based on radiographic images. Their study shows that AI can help detect peri-implant bone changes at an earlier stage, however, standardized imaging procedures are still important [34]. Therefore, AI makes objective measurements possible, reducing variability and improving early detection of bone loss around an implant. In the future, as AI continues to develop, it is expected to evolve as a very useful tool for clinicians in dental implant assessment.

G. AI in Implant Prognosis

Implant prognosis helps in predicting whether an implant will stay stable and keep functioning over the years. Traditionally, dentists estimate this risk from clinical factors such as patient's age, smoking habit, general health, bone quality and the type of implant used, all of which are linked to affect failure rates [14]. AI-based models bring these factors together with information from radiographs and estimate the chance of complications or failure, both before and after the implant is placed [12]. In one study, Zhang et al. (2023) trained a deep learning model (ResNet-50) on 1,080 periapical and panoramic radiographs from 248 patients. When both types of radiograph were used together, the model predicted implant failure with an accuracy of 87%, which was better than when either type was used alone [13]. Al Hendi et al. (2024) also pointed out that AI is now being used to predict implant success and to study osseointegration, although the small size of the available datasets remains a real limitation [25]. Tools of this kind may help dentists spot implants at risk early, but they need to be tested on larger datasets from several centres before they can be used in everyday practice.

Table I organises the principal studies referenced in this review by clinical focus, technique used, and their primary contribution to the field.

V. RESEARCH GAPS AND CURRENT LIMITATIONS

Although artificial intelligence has shown promising results in implant dentistry, several limitations still need to be addressed before it can become a routine part of clinical practice.

The first challenge is the availability of high-quality data. Many studies use images and records from only one institution, which may limit how well the AI system performs when used in other clinical settings. The datasets collected from different hospitals and clinics also need to be processed for improved reliability and accuracy.

TABLE I Principal studies referenced in this review, by clinical focus, technique and main observation.

Ref. No.	Author and Journal Name	Focus area	Technique	Setting	Result/Observation

15	Ibraheem et al. (2024)	Implant fixture identification	CNN-based radiographic analysis	Systematic Review	The systematic review found out that CNN-based algorithms had very high accuracy in the recognition of various implant systems on radiographs. This approach may help to maintain prostheses and remove implants.
16	Li et al. (2024)	Tooth and implant-related radiographic analysis	YOLOv4 and CNN	Radiographic Imaging study	The use of YOLOv4 and CNN allowed achieving a very high level of accuracy in the detection and classification of teeth and dental implants on radiographs.
17	Kurt Bayrakdar et al. (2021)	Implant planning using CBCT	Deep learning/CNN	CBCT-based imaging study	The deep learning models helped to analyze the CBCT scans for implant planning by recognizing various anatomical structures and suitable places for implants.
19	Dawood et al. (2026)	Digital implant planning	Multiple AI models	Narrative Review	The review stated that the AI models have the potential to improve the process of implant planning due to the automation of such processes as interpretation of imaging, positioning, and design of surgical guides
23	Wang et al. (2024)	Tooth instance segmentation	Co-Mask R-CNN	Dental image analysis study	The application of Co-Mask R-CNN allowed segmenting instances of teeth in crowded dental images better than other traditional approaches to segmentation
24	Khan et al. (2022)	Vision transformer applications	Transformer-based AI	Comprehensive Survey	The review concluded that Vision Transformers showed competitive or even better results than CNNs in various tasks with the use of dental imaging
25	Al Hendi et al. (2024)	Prosthodontic rehabilitation	Machine learning and deep learning	Review	This review discussed how AI is used across prosthodontics, from diagnosis and CAD/CAM design of prostheses to treatment planning and predicting implant success. It also noted that small datasets limit its clinical use.
29	Ntovas et al. (2024)	Mandibular canal segmentation	AI-based segmentation model	Clinical CBCT evaluation	The AI segmentation model could recognize the mandibular canal on CBCT scans and improve the visualization of this structure and thus lower the risk of inferior alveolar nerve injuries during implant surgery.
30	Elgarba et al. (2024)	Automated virtual implant placement	AI-driven implant planning algorithm	Comparative preclinical study	The algorithm of implant planning based on the AI system was able to find positions of implants that were equivalent to those made by

					experienced clinicians but saved planning time.
34	Li et al. (2025)	Marginal bone loss around dental implants	Deep learning on dental radiographs	Systematic review and meta-analysis	This meta-analysis showed that AI models could predict marginal bone loss around implants from radiographs with high sensitivity and specificity, but stressed the need for standard imaging protocols.

Another aspect is the variation in how experts label and interpret various radiographic images. If different clinicians identify the same anatomical structures differently, then the AI system may learn inconsistent information during training.

A third limitation is that many studies focus on technical accuracy rather than the patient wise outcomes. While an AI model may perform well in image analysis, it is still important to determine whether its use actually improves the treatment success and patient care.

The lack of transparency in some AI systems is also a concern. Clinicians also need to understand how recommendations are generated before they can confidently use these tools in practice.

Finally, most AI applications currently focus on a single task such as implant detection or image segmentation rather than a holistic view. Fully integrated systems capable of handling the entire implant planning process have not yet been thoroughly tested in real clinical environments.

VI. FUTURE DIRECTIONS FOR AI-ASSISTED IMPLANT PLANNING

The effective success of AI in implant dentistry depends on continued improvements in research, technology, and clinical validation.

Stage 1: Better Data Collection

Researchers should develop larger databases that include CBCT scans, radiographs, intraoral scans, and patient records from multiple institutions with uniform labeling. More diverse data can improve the accuracy and reliability of AI systems.

Stage 2: Standardized Labelling

Dental specialists should work in collaborations to create clear guidelines for image annotation. Consistent labeling will help AI models learn more accurately and reduce errors.

Stage 3: Improvement of Individual AI Tools

Different AI applications such as tooth detection, implant identification, bone measurement, nerve canal detection etc. should continue to be refined and tested separately before being combined into larger systems.

Stage 4: Clinical Testing

AI models should be evaluated using labeled datasets from different institutions and patient populations. Clinical studies are necessary to determine whether these tools provide meaningful benefits in everyday practice.

Stage 5: Integration into Clinical Software

Future AI systems should be integrated into existing implant-planning software. Rather than replacing clinicians, these systems should provide suggestions that can be reviewed and modified by the dentist before final decisions are made.

VII. SUMMARY OF AI TECHNIQUES

Table II shows the main AI techniques discussed in this review and compares them side by side. For each technique, the authors have listed what the model does, where it is used in implant dentistry, the kind of data it needs for training and its main drawback. CNNs and U-Net are the most widely used, mainly for recognising teeth and implants and for outlining bone, nerve canals and sinuses on CBCT scans [10], [18]. YOLO and Faster R-CNN are suited to locating missing teeth and implants on radiographs [20], [21], while Mask R-CNN can detect and outline each implant separately [22]. Vision transformers have been reported to be promising for combining different types of patient data, and need larger datasets and have not yet been tested thoroughly in dentistry [24]. In practice, the choice of technique depends on the clinical requirements and on how much labelled data is available.

TABLE II Comparison of the principal AI architectures used in dental implant imaging.

Technique	Primary function	Dental implant application	Typical data requirement	Key limitation
CNN	Image classification and feature extraction	Tooth/implant recognition; radiographic diagnosis	Thousands of labelled radiographs	Limited global context
U-Net	Pixel-level semantic segmentation	Bone, canal, sinus, and edentulous region outlining	Annotated CBCT slice pairs	Sensitive to annotation inconsistency
YOLO	Real-time object detection	Missing tooth and implant detection in panoramic images	Labelled bounding-box datasets	May miss small or overlapping structures
Faster R-CNN	Region proposal + classification	Detailed cross-sectional and panoramic analysis	Region-annotated image sets	Higher computational cost
Mask R-CNN	Instance detection plus per-object mask	Simultaneous implant detection and outlining	Pixel-level instance labels	Computationally demanding
Vision Transformer	Global image and sequence understanding	Multimodal data fusion; integrated treatment prediction	Very large diverse datasets	Limited dental validation

VIII. CONCLUSION

Artificial intelligence has become an increasingly important tool in dentistry and medicine and its involvement in implant planning and prosthodontic rehabilitation can help the dentist significantly. Current research shows that AI can assist the dentist in several areas including image analysis, implant identification, bone evaluation, and treatment planning. Such applications have the potential to improve efficiency and reduce the time required for many clinical tasks.

Despite these advantages, AI can only be viewed as an assistance for professional judgment. Successful implant treatment primarily depends on the knowledge, experience, and decision-making skills of the dentist. AI is most effective when used as a supportive tool to help dentists perform traditional tasks more efficiently and consistently.

As research continues and larger clinical studies become available, AI can play a greater role in implant dentistry. For dental students and future practitioners, experience and understanding of AI tools for its benefits and limitations will be essential. AI has the potential to improve patient care and become a valuable part of modern dental practice, only after proper validation and responsible use,.

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