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# Artificial Intelligence, Cone-Beam Computed Tomography (CBCT) and Digital Twins for Predicting Biological and Prosthetic Complications Before Implant Placement: A Narrative Review

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## Abstract

Despite advances in digital implant planning, biological and prosthetic complications remain difficult to anticipate prior to implant placement because conventional workflows largely rely on static anatomical information. This narrative review examines whether emerging computational technologies, including artificial intelligence, Digital Twins, radiomics and deep learning, can support predictive, patient-specific planning and the preoperative estimation of implant complications. Literature published within the last five years was retrieved from PubMed, Embase and Web of Science and evidence from clinical, computational, experimental, imaging-based and systematic review sources was synthesized. For biological outcomes, models built on integrated patient data perform well, with reported accuracies up to 94.5% and areas under the curve above 0.90 for implant survival, peri-implantitis, marginal bone remodeling and osseointegration; however, external validation is limited and prosthetic complication prediction remains comparatively underdeveloped. Digital Twins provide a dynamic framework that integrates anatomical, functional and biomechanical data to support risk assessment and treatment simulation, while radiomics and deep learning convert CBCT into quantitative bone-quality biomarkers. Current evidence indicates that artificial intelligence cannot yet predict implant failure with certainty before placement, but it can meaningfully enhance risk assessment and advance personalized, predictive implant dentistry.

**Keywords:** Dental Implants; Artificial Intelligence; Cone-Beam Computed Tomography; Digital Twin; Peri-Implantitis

## Introduction

Dental implant therapy has become a valuable option for oral rehabilitation, offering esthetic benefits together with improved retention and stability and thereby restoring masticatory function [1]. Achieving optimal outcomes, however, requires a high degree of precision and the growing demand for implant therapy has driven the digitalization of planning workflows [2]. These digital workflows improve the accuracy and efficiency of successive treatment stages by integrating three-dimensional imaging, computer-aided planning and guided surgery, enabling accurate diagnosis, prosthetically driven implant placement and a more streamlined prosthetic design process [3].

Radiographic assessment is central to both planning and postoperative evaluation because it provides objective information on bone morphology and implant stability [4]. Cone-Beam Computed Tomography (CBCT) has become the imaging modality of choice because it provides three-dimensional visualization of the alveolar bone and adjacent anatomical structures. Nevertheless, image artifacts, radiation exposure and interobserver variability remain important limitations of CBCT-based assessment [5].

Among technological advances in implant dentistry, guided implant surgery has emerged as a promising approach that improves placement predictability and safety by transferring the virtual plan to the surgical field [5]. Guided surgery is broadly classified as static or dynamic [6]. The static approach relies on a prefabricated surgical guide designed from the virtual plan, which constrains the drilling trajectory during surgery but does not allow intraoperative modification of the planned implant position [7].

Beyond surgical accuracy, implant success depends on a complex interaction of patient-related, biological and mechanical factors. Bone quality, bone remodeling dynamics, systemic conditions, smoking, soft tissue characteristics and the peri-implant tissue response all influence long-term outcomes, so even an ideally positioned implant may fail because these variables cannot be fully assessed through conventional anatomy-based planning [8]. Although conventional digital planning has substantially improved surgical precision, its static, anatomy-centered nature limits its ability to anticipate the dynamic biological processes that ultimately determine long-term implant success [7].

To date, no narrative synthesis has connected these rapidly evolving computational tools to the specific problem of estimating both biological and prosthetic complications before the implant is placed; the evidence remains dispersed across imaging, computational and clinical literatures and its real predictive value and limitations are therefore difficult for clinicians to judge. This gap provides the rationale for the present review. Accordingly, this narrative review examines whether emerging computational technologies, including artificial intelligence, Digital Twins, radiomics and deep learning, can support predictive, patient-specific planning and the preoperative estimation of implant complications and it evaluates the performance and current limitations of these approaches.

**Digital Twins in Implant Dentistry**

Even as digital implant dentistry has matured, most clinical workflows still depend on information captured at a single moment in time. Such snapshots cannot represent the biological, functional and biomechanical changes that unfold while an implant heals and is loaded and this shortfall has motivated a conceptual shift away from the static Virtual Patient and toward the Digital Twin [9]. In this newer paradigm, imaging, clinical and functional data streams are merged into a virtual model that is continuously refreshed over time, creating the informational basis for precision implant dentistry and for anticipating outcomes rather than merely recording them [10].

The Virtual Patient and the Digital Twin are related but differ in temporal and functional scope. A Virtual Patient is a three-dimensional reconstruction derived from CBCT, Intraoral Scans (IOS), facial scans, occlusal records, photogrammetry, virtual articulators and virtual facebows, enabling anatomical representation for diagnosis, prosthetically driven planning, guided surgery and virtual rehabilitation [11]. It remains inherently static, reflecting a single time point without continuous biological updating. The Digital Twin, by contrast, is a dynamic and continuously updated patient-specific model that extends beyond anatomy by incorporating functional, biomechanical and clinical data; continuous synchronization enables scenario simulation, adaptive treatment planning and real-time data integration and it constitutes the digital infrastructure for artificial intelligence-driven prediction of biological and prosthetic outcomes before implant placement [9,10].

Digital Twin construction relies on integrating multimodal datasets into a unified ecosystem. CBCT provides volumetric assessment of osseous structures for implant positioning [12]. Intraoral scanners deliver high-resolution surface geometry, although their accuracy depends on scanning strategy and clinical conditions [11]. Facial scanning introduces soft tissue and esthetic parameters, while digital occlusion systems capture static and dynamic functional relationships [12]. Integration of DICOM and STL datasets is essential for spatial alignment and generation of a coherent model for prosthetically driven planning [13].

Beyond anatomical reconstruction, biomechanical simulation using Finite Element Analysis (FEA) enhances predictive capability by evaluating stress distribution, micromotion and bone-implant interface behavior under functional loading [14]. These analyses support the optimization of implant positioning and prosthetic design, although their accuracy depends on assumptions about material properties, boundary conditions and bone behavior, underscoring the need for standardized modeling frameworks and clinical validation [15].

Clinical translation of Digital Twins nonetheless remains limited. Interoperability between heterogeneous digital systems is suboptimal, standardized protocols for acquisition, processing and validation are lacking and robust prospective evidence is required to establish predictive validity; economic and computational demands further constrain adoption [16]. Future implementation will depend on improved interoperability, standardized validation pathways and clinically relevant outcome metrics, including FDI (World Dental Federation) criteria for biological and prosthetic assessment. In summary, Digital Twins integrate anatomical, functional and biomechanical data into a continuously updated, patient-specific model that provides the substrate for artificial intelligence-based prediction of biological risk prior to implant placement (Fig. 1) [13,14].

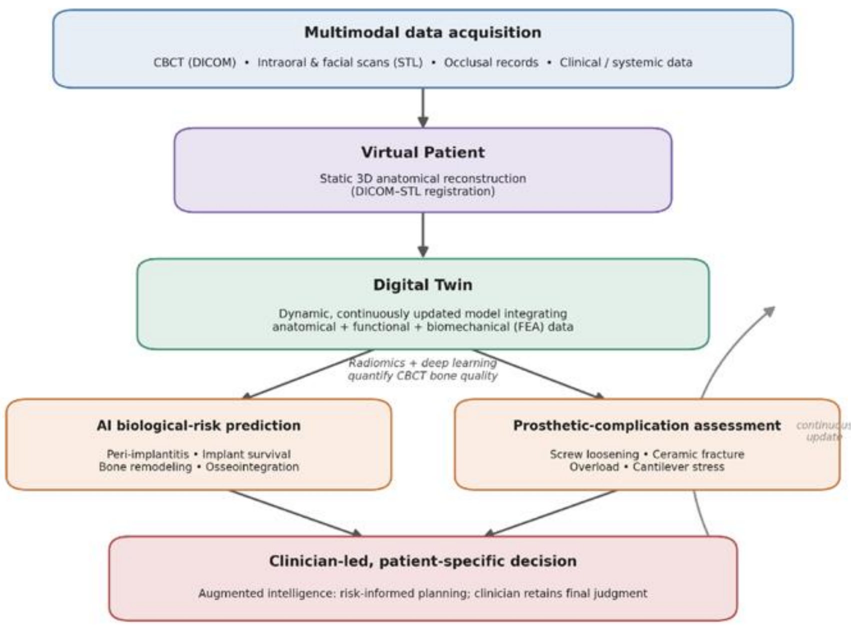


**Figure 1:** Integrated Digital Twin workflow for predictive implant planning. Multimodal data are consolidated into a Virtual Patient and then a continuously updated Digital Twin; radiomics and deep learning quantify CBCT bone quality to feed artificial intelligence models that estimate biological and prosthetic complications, informing a clinician-led, patient-specific decision within an augmented-intelligence framework.

## Artificial Intelligence for Biological Risk Prediction

Once a Digital Twin consolidates a patient's imaging and clinical data, the same information can be used to estimate the likelihood that an implant will develop biological complications before it is placed [9,11]. Prediction models learn the relationships among systemic health, radiographic findings and site-specific factors to flag complications consistent with the FDI biological criteria, shifting the clinician from reacting to complications toward anticipating them [15,16]. Four areas currently show the strongest evidence, summarized in Table 1.

### *Peri-Implantitis Prediction*

Peri-implantitis is the biological outcome most frequently modeled, appearing in four of fourteen recent prediction studies [17]. The predictors are clinically intuitive: a history of periodontitis, implant position, plaque control, width of keratinized mucosa and blood glucose [18]. A random-forest model separated at-risk from healthy cases with an Area Under the Curve (AUC) of 0.71 and correctly classified roughly 70% of cases, with functional time and oral hygiene carrying the greatest weight [19]. Nomograms have extended this capacity for higher-risk patients, such as those with diabetes or a history of severe periodontitis

[15]. Advanced knowledge of this risk allows clinicians to tailor maintenance and intervene early, in line with FDI thresholds for bleeding, suppuration and bone loss [15,20].

*Implant Survival Prediction*

Survival models take a broader view, incorporating systemic health, bone quality and implant dimensions to estimate long-term prognosis [16]. A neural network weighing 55 parameters predicted single-implant survival with 94.5% accuracy, well above simpler models that reached 74.1% [16]. Radiograph-based and web-based tools have reported comparable performance in forecasting failure and peri-implant disease, frequently exceeding an AUC of 0.90 [20]. Smoking, systemic disease and residual periodontal pockets recur as predictors [16,17]. A key limitation is that only three of the fourteen models were tested on external data, so these figures should inform, rather than replace, clinical judgment [21].

*Bone Remodeling Prediction*

Marginal bone loss is one of the clearest FDI indicators of osseous adaptation and three reviewed studies built models around it [17]. Support-vector and neural-network approaches predicted it with AUC values of 0.967 and 0.928 and specificity as high as 100%, drawing on radiographic and trabecular detail [22]. Convolutional neural networks reading radiographs have detected peri-implant bone changes with over 90% accuracy, converting a subjective assessment into a measurable one [19]. This allows the team to anticipate bone behavior and adjust loading or design before problems arise [23].

*Osseointegration Prediction*

The final domain estimates whether bone will bond to the implant before loading [19]. Seven deep-learning models applied to plain radiographs of 1,206 implants reached a peak accuracy of 0.896, with AUC between 0.890 and 0.922 [19]. Sensitivity and specificity were approximately 0.78-0.86 [24]. Systems that pair bone mineral density with insertion-torque readings support the view that images alone can indicate primary stability [16]. This offers a low-radiation means of gauging stability during planning [25].

Taken together, deep learning and convolutional models consistently outperform earlier statistical methods, yet bias, single-center datasets and limited interpretability limit routine use [15,17]. Before these predictions can be trusted at the planning stage, standardized, externally validated models built around FDI outcomes are needed [16]. Because much of this capability depends on information extracted from radiographs, the next section considers how radiomics and deep learning interpret those images [26].

| **Biological Outcome** | **Modeling Approach** | **Reported Performance** | **Key Predictors** | **Ref.** |
|---|---|---|---|---|
| Peri-implantitis | Random forest; risk nomograms | AUC ≈ 0.71; ≈ 70% of cases correctly classified | History of periodontitis, implant position, plaque control, keratinized mucosa width, blood glucose | [18,19] |
| Implant survival | Artificial neural network (55 parameters); web-based tools | Accuracy up to 94.5%; AUC frequently > 0.90 | Systemic disease, smoking, bone quality, residual periodontal pockets, implant dimensions | [16,20] |
| Marginal bone remodeling | Support-vector machine; neural networks; CNN on radiographs | AUC 0.928–0.967; specificity up to 100%; > 90% accuracy | Radiographic and trabecular bone detail | [19,22] |
| Osseointegration | Deep-learning models on plain radiographs (n = 1,206) | Peak accuracy 0.896; AUC 0.890–0.922; | Radiographic bone pattern; bone mineral density paired with insertion torque | [16,19,24] |

| Biological Outcome | Modeling Approach | Reported Performance | Key Predictors | Ref. |
|---|---|---|---|---|
| | | sensitivity/specificity ≈ 0.78–0.86 | | |

**Table 1:** Representative artificial intelligence models for the preoperative prediction of biological implant outcomes. AUC, area under the curve; CNN, convolutional neural network. Performance figures are drawn from the cited studies and are largely based on internal validation.

**Radiomics and Deep Learning for Bone Characterization from CBCT**

Assessment of bone quality is a fundamental component of preoperative implant planning because it directly influences implant selection, the surgical approach and drilling protocols. Although CBCT is a cornerstone of planning, its interpretation remains largely qualitative, relying on visual assessment of bone volume, anatomical limitations and surgical feasibility [27]. Within the Digital Twin framework, radiomics and deep learning expand the diagnostic potential of CBCT by transforming images into quantitative information, thereby providing imaging biomarkers associated with biological risk and bone quality prior to implant placement [23,25].

Radiomics is the computational extraction of quantitative features from medical images, including intensity-, texture- and shape-based parameters. In implantology, these features identify subtle variations in trabecular organization, cortical morphology and structural heterogeneity that are not always detectable on conventional radiographs, complementing the traditional evaluation based on alveolar ridge height and width with a more comprehensive characterization of the recipient site [25,26].

One of the most relevant applications is the analysis of trabecular bone microarchitecture. Parameters such as bone density, texture, trabecular connectivity and structural heterogeneity influence functional load distribution and the achievement of primary stability [27]. Quantifying these characteristics can provide additional information on bone quality even at sites with similar dimensions on conventional CBCT, supporting decisions on implant design, drilling protocol, anticipated insertion torque, healing time and prosthetic loading strategy [24].

Cortical bone thickness is another clinically significant parameter, as the cortical plate is critical for initial mechanical stability, particularly in regions of low trabecular density [28]. Automated or semi-automated assessment of cortical thickness may improve reproducibility and reduce variability in subjective interpretation and a thin or irregular cortical layer may be associated with an increased risk of micromovement, marginal bone remodeling or the need to modify surgical and prosthetic loading protocols [25].

Deep learning, particularly Convolutional Neural Networks (CNNs), further extends CBCT analysis by enabling automatic segmentation, recognition of anatomical structures and identification of complex patterns associated with bone quality [29]. These models can reduce interobserver variability and generate objective quantitative information that, integrated into a Digital Twin, enriches the patient-specific representation with structural and biomechanical parameters before surgery, supporting more comprehensive planning and potentially improving long-term success [30].

Clinical implementation nonetheless requires caution. Radiomic features may be influenced by voxel size, acquisition parameters, segmentation methods and CBCT artifacts, so standardized imaging protocols, external validation and explainable artificial intelligence are prerequisites for routine use [24,25]. Overall, radiomics and deep learning represent a step toward more objective and personalized planning by converting CBCT data into quantitative indicators of bone quality and this structural characterization also provides the basis for understanding and predicting prosthetic complications [31,32].

**Predicting Prosthetic Complications**

Whereas biological prediction is comparatively advanced, prediction of prosthetic complications remains less developed, in part because the underlying events are mechanical and depend on design and loading variables that are harder to capture from preoperative imaging alone [33]. Understanding these complications is nonetheless essential, because they can be anticipated through careful planning and represent the mechanical counterpart to the biological risks addressed above [34].

Abutment screw loosening is among the most common mechanical complications. The abutment screw secures the abutment to the fixture and maintains the stability of the implant-abutment interface; repetitive functional and occlusal loading gradually reduces screw preload and increases the likelihood of loosening, which, if uncorrected, may lead to prosthetic instability, discomfort, peri-implant inflammation, screw fracture or restoration failure [35]. Risk is influenced by screw design, material properties, connection accuracy and implant location, with posterior implants being more susceptible due to higher masticatory forces [36]. Prevention relies on accurate placement, precise anti-rotational connections and the application of the manufacturer's recommended torque with a calibrated wrench; retightening after initial torque can compensate for preload loss due to embedment relaxation [27].

Fracture of the ceramic restoration represents a further technical concern. Clinicians frequently select zirconia because it combines favorable esthetics with biocompatibility, resistance to corrosion and high fracture toughness and because it does not produce the grayish shadowing of the peri-implant mucosa that can accompany metal substructures [37]. The historical weak point lay in the porcelain veneer layered over zirconia frameworks, which is prone to chipping; monolithic zirconia restorations were subsequently developed to eliminate that veneer altogether, lowering the chipping risk while preserving acceptable strength and appearance. Resistance to fracture additionally reflects the choice of abutment material and the angulation of the implant, although the available evidence indicates that moderate angulation still yields clinically acceptable performance [38].

Occlusal trauma and mechanical overload have been associated with progressive marginal bone loss and, in severe cases, loss of osseointegration. Excessive cyclic loading may produce micro-wear at the implant-abutment interface, releasing particles that stimulate inflammatory reactions in peri-implant tissues [39]. Marginal bone loss ranges from approximately 0.65 to 1.20 mm under normal occlusal conditions and may reach 3 mm under traumatic overload, while parafunctional habits such as bruxism and unfavorable occlusal schemes increase biomechanical stress; overload frequently acts synergistically with bacterial biofilm to accelerate tissue destruction and raise the risk of peri-implantitis, so careful occlusal adjustment and individualized prosthetic planning are essential [40].

Cantilever extensions are often used in implant-supported fixed partial dentures to reduce the number of implants or avoid additional grafting [41]. They offer practical and economic advantages but generate greater bending forces and stress concentrations around supporting implants and finite element analyses show that crestal bone stress increases with cantilever length, potentially contributing to bone resorption, prosthetic complications and implant failure; cantilever length should therefore be minimized and occlusal forces carefully distributed [42,43].

Occlusal force finally plays a central role in implant biomechanics. After placement, force distribution within the arch changes, particularly in free-end edentulous cases and bite force is influenced by muscle strength, tooth arrangement, implant position and bone quality [44]. Controlled functional loading may stimulate bone remodeling and support osseointegration, whereas excessive force increases the risk of mechanical complications, marginal bone loss and failure. Because loads are transmitted from the crown through the abutment to the implant and bone, accurate assessment of bite force and occlusal adjustment remains fundamental to planning [31,45].

**Conclusion**

Implant planning is shifting from a discipline anchored in static images toward intelligent platforms that combine anatomical, biological and functional data for individualized decisions. This review followed that arc-from CBCT-based anatomical planning, to Digital Twins that personalize the virtual patient, to artificial intelligence models that estimate biological risk supported by radiomics and deep learning and finally to the prediction of prosthetic complications-raising a central question: can these tools be integrated into fully autonomous implant planning or will clinical judgment remain indispensable?

Current evidence points to increasing automation rather than full autonomy. Artificial intelligence already performs discrete pre-surgical tasks well, particularly anatomical segmentation, landmark identification and virtual patient creation and when applied to CBCT it can improve recognition of critical structures, raise diagnostic confidence and help prevent neural injury, thereby enhancing both efficiency and clinical safety. No study, however, has yet demonstrated or validated a fully autonomous planning protocol. The realistic trajectory is therefore one of augmented intelligence, in which artificial intelligence, Digital Twins, radiomic analysis and predictive models extend the clinician's diagnostic and planning capacity while the clinician integrates biological and prosthetic factors with patient preferences and retains responsibility for the final decision.

**Future Implications and Challenges**

Several obstacles must be addressed before these technologies enter routine practice. Chief among them are the limited clinical validation of existing models, the scarcity of prospective studies, poor interoperability between heterogeneous digital systems and the absence of standardized, externally validated protocols built around clinically meaningful outcomes such as the FDI criteria. Most predictive models have been trained and tested on single-center data, which constrains their generalizability and their interpretability remains limited. Encouragingly, recent work indicates that artificial intelligence can already be coupled with dynamic navigation and mixed-reality systems to assist both planning and surgical execution, signaling a move toward progressively more intelligent workflows, although these technologies still require validation in larger studies before becoming standard of care. Realizing this potential will depend on multicenter external validation, standardized acquisition and modeling frameworks, explainable artificial intelligence and prospective evidence linking predictions to long-term biological and prosthetic outcomes.

**Conflict of Interest**

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

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**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**

Not applicable.

**Authors' Contributions**

All authors contributed equally to this paper.

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