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Systematic Review

Clinical readiness and generalizability of artificial intelligence in implant dentistry: a systematic review of diagnostic accuracy, treatment planning, prognosis and external validation

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ABSTRACT

Artificial intelligence (AI) is increasingly being incorporated into digital dentistry. In implant dentistry, machine-learning and deep-learning systems have been investigated for radiographic diagnosis, anatomical segmentation, treatment planning, prosthetically driven implant positioning, and prediction of implant-related outcomes. To systematically evaluate the clinical applications of AI in implant dentistry, with particular emphasis on diagnostic accuracy, treatment planning, prognosis, external validation, generalizability, and clinical applicability. A systematic review will be conducted according to PRISMA 2020. PubMed/MEDLINE, Scopus, Web of Science, Embase, and Cochrane Library will be searched from inception to the final search date. Studies evaluating AI, machine learning, deep learning, neural networks, or related computational approaches in human implant dentistry will be considered. Diagnostic studies will be assessed using QUADAS-[2], prognostic studies using QUAPAS where applicable, and prediction-model studies using PROBAST+AI. Reporting quality of prediction models will be assessed using TRIPOD+AI. Current evidence demonstrates promising AI performance in anatomical segmentation, CBCT analysis, implant treatment planning, prosthetically driven positioning, and prediction of implant-related outcomes. However, the literature is heterogeneous with respect to datasets, algorithms, reference standards, outcome definitions, validation procedures, and performance measures. Many studies remain retrospective, and external validation and evidence of clinical utility are comparatively limited. AI has considerable potential as a decision-support technology in implant dentistry. The principal research priority is now progression from technical accuracy toward externally validated, explainable, calibrated, clinically useful, and patient-centered AI systems. Keywords AI; machine learning; deep learning; dental implants; implant dentistry; CBCT; implant planning; implant prognosis; peri-implantitis; digital dentistry.

Keywords: Artificial intelligence, Machine learning, Deep learning, Dental implants, Implant dentistry, CBCT, Implant planning, Implant prognosis, Peri-implantitis, Digital dentistry

INTRODUCTION

Traditionally, implant treatment planning was based predominantly on clinical examination, diagnostic casts, conventional two-dimensional radiography, and clinician experience. The introduction of computed tomography and, subsequently, cone-beam computed tomography (CBCT) represented a major advancement by enabling three-dimensional assessment of residual bone dimensions and the spatial relationships of critical anatomical structures.[1,2] The subsequent integration of intraoral scanning, computer-aided design and computer-aided manufacturing (CAD/CAM), digital diagnostic wax-ups, facial scanning, and computer-assisted implant surgery has further transformed implant workflows, facilitating increasingly integrated and prosthetically driven treatment planning.

AI represents a further evolution of this digital transformation. Machine-learning algorithms can identify complex patterns and relationships within structured and unstructured datasets, whereas deep-learning approaches can automatically derive hierarchical representations from large and complex image datasets.[3,4] In implant dentistry, these capabilities have generated increasing interest in applications ranging from radiographic interpretation and anatomical segmentation to implant-site assessment, treatment planning, prosthetically driven implant positioning, and prediction of implant-related outcomes.

Recent systematic reviews have demonstrated promising applications of AI in dental implant planning and prognosis.[5-10] AI-based systems have shown potential for assisting with anatomical assessment, identifying implant sites, estimating available bone, supporting implant positioning, and predicting outcomes such as implant failure and peri-implant disease. However, reported technical performance alone does not establish clinical readiness. A model may demonstrate high accuracy within a development dataset yet perform differently when applied to patients from another population, institution, imaging environment, or clinical workflow.

The clinically important question has therefore evolved beyond whether AI can perform a particular implant-related task. The more consequential question is whether these systems are sufficiently valid, externally validated, generalizable, calibrated, interpretable, and clinically useful to support routine implant care. This distinction is particularly important in implant dentistry because AI-assisted recommendations may influence irreversible diagnostic and surgical decisions, including implant position, angulation, depth, and proximity to critical anatomical structures.

External validation is consequently a central component of clinical AI evaluation. A model developed and tested within a single dataset may demonstrate excellent internal performance while failing to maintain accuracy when exposed to differences in patient characteristics, disease prevalence, imaging equipment, acquisition protocols, operator expertise, or institutional treatment practices. Similarly, predictive models should not be evaluated solely on measures of discrimination; calibration, clinical utility, decision consequences, and transportability are essential considerations when predictions are intended to influence patient management.

Accordingly, the present systematic review focuses on the clinical readiness of AI across the implant treatment pathway, with particular emphasis on diagnostic accuracy, anatomical assessment, treatment planning, prosthetically driven implant positioning, prognosis, external validation, calibration, interpretability, and generalizability. By distinguishing technical algorithmic performance from clinically meaningful evidence, this review aims to identify the current strengths of implant-related AI, characterize the methodological limitations of the existing literature, and determine the evidence required for responsible translation of AI from experimental development into routine clinical practice.

AI applications in implant diagnosis

AI-based image analysis represents one of the most extensively investigated applications of AI within implant dentistry. The increasing availability of three-dimensional imaging, particularly CBCT, has created substantial opportunities for the application of machine-learning and deep-learning algorithms to the analysis of implant-related anatomical and pathological information.[3,4] AI-based systems have been investigated for a range of diagnostic and image-analysis tasks, including identification of edentulous regions, assessment of available bone, anatomical segmentation, detection of peri-implant bone changes, identification of existing implants, and recognition of clinically relevant pathological findings.[3,4]

CBCT has become an important imaging modality in contemporary implant diagnosis because it provides volumetric information regarding the residual alveolar ridge and its relationship with critical anatomical structures.[1,2] However, interpretation of three-dimensional datasets can be time-consuming and requires considerable clinical experience. AI offers the possibility of automating selected image-analysis processes and converting complex radiographic datasets into structured anatomical information that can subsequently be incorporated into treatment planning.[3,4]

Deep-learning algorithms are particularly suited to image-based tasks because they can learn spatial and morphological features from large collections of annotated images.[3,4] Within implant-related CBCT analysis, AI has been investigated for identifying and delineating anatomical structures, evaluating bone dimensions, and assisting with recognition of structures relevant to implant placement.[5,6] Such systems have the potential to facilitate the initial assessment of implant sites and reduce repetitive manual image-processing tasks.[3,4]

Automated anatomical segmentation is an important application because accurate identification of critical structures is fundamental to safe implant planning.[3,4] Deep-learning approaches have been investigated for segmentation of structures including the mandibular canal and maxillary sinus.[5,6] Automated delineation may reduce the time required for manual tracing and potentially improve consistency between assessments.[3,4]

Segmentation performance, however, should be interpreted in relation to the clinical purpose for which the segmented structure will be used.[3,4] A model may demonstrate favorable numerical performance while still producing clinically relevant errors at anatomically critical boundaries. Small inaccuracies in the delineation of a structure such as the mandibular canal may have greater clinical significance than comparable errors in a noncritical anatomical region. Therefore, evaluation of segmentation systems should consider not only statistical overlap measures but also their potential influence on subsequent clinical decisions.[3,4]

Beyond preoperative assessment, AI has potential applications in the evaluation of existing implants and peri-implant tissues.[6,10] Algorithms have been investigated for recognizing dental implants within radiographic images and for identifying changes in peri-implant bone.[10,11] Automated detection and quantification could potentially support standardized longitudinal assessment and assist clinicians in identifying findings that warrant closer evaluation.[10,12]

However, the clinical interpretation of peri-implant bone changes requires consideration of factors beyond image appearance alone.[10,11] Implant position, radiographic angulation, image quality, restorative status, previous bone levels, and clinical findings may influence interpretation. AI-based radiographic analysis should therefore complement rather than replace comprehensive clinical assessment.[3,4]

Despite the potential advantages of AI-based image analysis, diagnostic performance may vary substantially according to the characteristics of the underlying dataset.[3,4] Image quality, voxel size, metallic artifacts, anatomical variation, scanner characteristics, acquisition protocols, and differences in patient populations can all influence algorithmic performance.[4,10] Metallic components associated with existing implants may generate artifacts that obscure adjacent anatomical structures and potentially challenge automated segmentation or detection.[10,11]

Another important consideration is dataset representativeness.[3,4] An algorithm trained using images from a single institution or a limited range of imaging systems may learn characteristics that are specific to that dataset rather than universally applicable anatomical patterns. Consequently, high performance on an internal test set should not automatically be interpreted as evidence of generalizability.[3,4]

AI-generated diagnostic information should currently be regarded as an adjunct to, rather than a replacement for, professional clinical interpretation.[3,4] Automated segmentation, anatomical measurements, implant identification, and radiographic findings should be reviewed by an appropriately trained clinician, particularly when the output has implications for surgical planning or proximity to critical anatomical structures.[5,7]

The appropriate clinical role of AI is therefore not simply to automate image interpretation, but to augment clinician capability by reducing repetitive tasks, highlighting relevant information, and potentially improving consistency.[3,4] The extent to which these theoretical advantages translate into improved diagnostic accuracy, reduced errors, increased efficiency, or better patient outcomes requires rigorous validation in representative clinical environments.[5,7]

AI in implant treatment planning

AI-assisted implant treatment planning has emerged as an important area of research within digital implant dentistry.[5,7,8] The increasing availability of three-dimensional imaging and digitally integrated restorative workflows has created opportunities for AI systems to support multiple stages of implant planning, extending from identification of suitable implant sites to the selection and positioning of implants.[5,7] Current applications have investigated automated or semi-automated assessment of edentulous regions, evaluation of available bone, implant selection, determination of implant angulation and depth, and analysis of the spatial relationship between the proposed implant and adjacent anatomical structures.[5-8]

The assessment of available bone is particularly important because implant dimensions and position must be compatible with the three-dimensional anatomy of the residual ridge.[5,7] AI systems can potentially assist in estimating bone dimensions and identifying anatomical limitations from CBCT data.[5,6] Alqutaibi et al reported promising performance of AI-based approaches for dental implant planning, particularly in the identification of edentulous regions and assessment of bone dimensions on CBCT.[5] These findings support the potential role of AI as an adjunct during the initial stages of implant treatment planning.[5,7]

One of the major potential advantages of AI-assisted planning is its ability to integrate multiple sources of patient-specific information. CBCT provides three-dimensional anatomical data, while intraoral scans and digital diagnostic wax-ups provide information regarding the dentition, soft-tissue contours, and intended restorative outcome. When these datasets are combined, AI could potentially assist in interpreting the relationship between the proposed restoration and the underlying anatomy.

Prosthetically driven implant planning is particularly relevant to prosthodontics because the ideal implant position cannot be determined exclusively by the available bone. The implant must ultimately support a restoration that satisfies functional, biological, aesthetic, and mechanical requirements. Implant position therefore needs to be considered in relation to the planned emergence profile, restorative space, occlusal relationships, aesthetics, and access for oral hygiene.

AI may potentially integrate the proposed prosthetic design with three-dimensional anatomical information to assist in identifying an implant position that accommodates both restorative and anatomical requirements. Such an approach could facilitate a more comprehensive planning strategy in which the desired prosthetic outcome influences the surgical position rather than being considered only after implant placement.

In the aesthetic zone, implant positioning must satisfy particularly demanding restorative requirements. The three-dimensional location of the implant influences the emergence profile, crown contour, soft-tissue architecture, interproximal relationships, and overall aesthetic result.

Nevertheless, the clinical significance of an AI-generated implant position depends on the reference criteria used to define an appropriate position.[5,7] An algorithm trained primarily to optimize anatomical parameters may not necessarily produce the position that is optimal from a restorative or prosthodontic perspective.[5,7] Therefore, evaluation of AI planning systems should consider the clinical objective of implant positioning rather than relying solely on computational similarity/geometric accuracy.[5,7]

AI-assisted systems that incorporate digital wax-ups, intraoral scans, and CBCT information may therefore provide an opportunity to evaluate these factors simultaneously.[2,5] However, the available evidence should be interpreted cautiously because technical capability does not necessarily demonstrate clinical effectiveness, improved treatment outcomes, or superiority over experienced clinician-based planning.[5,7,8]

Despite the rapid development of AI-assisted implant planning, several methodological issues limit the interpretation of current evidence. Many investigations remain retrospective and are performed within single institutions or relatively controlled datasets.[7,8]

A further limitation is the distinction between internal technical performance and genuine clinical generalizability. An AI system may demonstrate excellent performance when tested using data derived from the same environment in which it was developed,

Furthermore, AI-generated treatment plans should currently be considered recommendations requiring professional assessment rather than autonomous prescriptions.[3,4] Implant planning involves irreversible clinical decisions, and the clinician must remain responsible for evaluating anatomical risk, restorative feasibility, surgical complexity, patient preferences, and the limitations of the available evidence.[5,7,8]

Overall, AI-assisted implant treatment planning represents a promising development in digital implant dentistry. Current evidence suggests potential benefits in implant-site identification, bone assessment, anatomical analysis, and technical planning assistance.[5,7,8] The next stage of research should move beyond demonstrating whether AI can generate an implant plan and determine whether AI-assisted planning produces more accurate, safer, efficient, reproducible, and clinically beneficial treatment decisions when compared with established clinician-led digital workflows.[6]

AI in outcome prediction

AI-based outcome prediction represents rapidly developing application of machine learning within implant dentistry. Unlike diagnostic systems that primarily classify existing findings, predictive models aim to estimate the probability of future/clinically relevant outcomes. AI has been investigated for the prediction of implant survival and failure, peri-implantitis, peri-implant mucositis, marginal bone loss, osseointegration, and implant stability.[10,13,14]

These applications have the potential to support individualized risk assessment and assist clinicians in identifying patients or implant sites that may require closer monitoring or modified treatment strategies.

The long-term success of implant therapy is influenced by multiple interacting factors. Patient characteristics, systemic and local conditions, implant-related variables, surgical factors, prosthetic considerations, oral hygiene, and biological responses may collectively influence clinical outcomes. Machine-learning methods offer the potential to analyze multiple clinical, radiographic, and treatment-related variables simultaneously and identify patterns associated with particular outcomes.

Previous investigations have explored machine-learning approaches for predicting implant failure and peri-implant disease using clinical datasets.[11,12] Such models may potentially provide individualized estimates of risk rather than relying exclusively on population-level risk factors. In principle, this could support earlier identification of patients at increased risk and allow clinicians to consider preventive strategies, individualized maintenance schedules/closer clinical and radiographic surveillance.[11,12]

However, predictive association should not automatically be interpreted as clinical prediction.[15,16]

Peri-implantitis and peri-implant mucositis represent important complications in implant therapy, and their multifactorial nature makes them potential targets for machine-learning approaches. AI models may integrate demographic, clinical, radiographic, and treatment-related information to estimate an individual's probability of developing peri-implant disease.[11,12]

Nevertheless, the usefulness of such predictions depends on the quality and completeness of the predictors included in the model.[11,12]

Differences in disease definitions, follow-up duration, diagnostic criteria, and case selection can substantially affect apparent model performance.[15,16] Therefore, prediction studies should clearly define the outcome, establish an appropriate reference standard, and demonstrate that the model remains reliable when applied to populations different from those used during development.[15,16]

AI has also been investigated for predicting quantitative and biological outcomes such as marginal bone loss, osseointegration, and implant stability.[6,10] These applications are clinically relevant because they may provide information about the expected biological response to implant therapy.[6,10]

The prediction of such outcomes is particularly challenging because they may be influenced by multiple time-dependent and interacting factors.[6,10] Radiographic characteristics, implant-related variables, local anatomy, loading conditions, patient-related factors, and biological responses may all contribute to the observed outcome. AI models may be capable of integrating these variables within a single predictive framework.[6,10,11]

However, the clinical significance of a prediction model depends on whether its output can meaningfully influence treatment or follow-up decisions.[15,16] A statistically accurate prediction that does not alter clinical management or improve patient outcomes may have limited practical value.[15,16] Consequently, future studies should evaluate not only predictive performance but also clinical utility, calibration, generalizability, and the potential impact of AI-based predictions on patient management.[15,16]

A major consideration in evaluating AI-based prediction models is distinction between discrimination and clinical usefulness.[15,16] Measures such as area under receiver operating characteristic curve AUC) are frequently reported for this purpose.[15,16]

Although discrimination is important, AUC alone does not establish that prediction model provides accurate/ clinically useful risk estimates.[15,16] Two models may demonstrate similar discrimination while producing substantially different predicted probabilities. A model can therefore have a satisfactory AUC while remaining poorly calibrated.[15,16]

Calibration describes the agreement between predicted probabilities and the outcomes actually observed. Good calibration is particularly important when a model is intended to communicate individualized risk.[15,16]

External validation is one of the most important requirements for establishing the credibility of an AI prediction model.[15,16] A model developed using data from a particular institution may learn relationships that reflect the characteristics of that institution, patient population, diagnostic protocols, or treatment practices. When transferred to a different clinical environment, these relationships may not remain stable.[15,16]

External validation should therefore involve an independent dataset that was not used during model development.[15,16] Ideally, validation should assess performance across different institutions, patient populations, imaging protocols, and clinical environments. Multicentre validation and leave-one-centre-out approaches may provide particularly informative evidence regarding transportability.[15,16]

The need for external validation is especially important in implant dentistry because clinical practice varies considerably between institutions and practitioners. Differences in implant systems, surgical techniques, maintenance protocols, diagnostic criteria, imaging equipment, and patient characteristics may influence both predictors and outcomes. Consequently, strong performance within a single development dataset should not be interpreted as evidence that a model is ready for widespread clinical implementation.[15,16]

In implant dentistry, clinical utility could potentially be demonstrated if AI-assisted risk prediction improves patient selection, modifies maintenance strategies, supports earlier intervention, reduces complications, or improves treatment outcomes without creating unnecessary interventions. Such benefits must be demonstrated rather than assumed from statistical performance alone.[15,16]

Explainability is also increasingly relevant to predictive AI. Clinicians may be more likely to appropriately interpret an AI-generated risk estimate when they can understand which variables or features contributed substantially to the prediction. Explainable approaches may also assist in identifying inappropriate model behaviour and recognizing situations in which an algorithm should not be trusted.[15,16]

However, explainability should not be considered a substitute for rigorous validation. A model may provide an apparently understandable explanation while still being poorly calibrated or inadequately validated.[15,16]

The available evidence indicates that AI-based prediction in implant dentistry is promising, but the field remains in an important phase of the methodological development.[15,16]

A clinically credible AI prediction model should demonstrate appropriate outcome definition, robust model development, adequate internal validation, independent external validation, acceptable discrimination, satisfactory calibration, transparent reporting, and evidence of clinical utility.[15,16] Where possible, prospective evaluation and assessment of patient-centered outcomes should provide the final link between predictive performance and meaningful clinical benefit.[15,16]

Thus, the future of AI-based outcome prediction in implant dentistry lies not simply in developing increasingly complex algorithms, but in demonstrating that their predictions remain accurate, calibrated, transportable, interpretable, and the clinically actionable across real-world patient populations and the healthcare environments.[15,16]

External validation and generalizability

External validation represents a critical stage in determining whether an AI system developed in one clinical environment can be reliably applied to patients and data obtained from other environments.[15,16] In implant dentistry, this consideration is particularly important because AI models are frequently developed using relatively specific imaging datasets, patient populations, treatment protocols, and institutional workflows. High performance within the development dataset does not necessarily indicate that the model will retain its accuracy when exposed to clinically different data.[15,16]

During model development, internal validation is commonly performed using techniques such as data splitting, cross-validation, bootstrapping/ related resampling approaches.[15] These methods are useful for estimating how a model may perform on data that are similar to those used during development and can assist in identifying overfitting. However, internal validation cannot fully reproduce heterogeneity encountered when an AI system is transferred to independent clinical setting.[15,16]

External validation involves evaluating a previously developed model using an independent dataset that was not used during model development.[15,16] The external dataset may originate from a different institution, geographic region, patient population, imaging system, or period of clinical practice. Demonstration of consistent performance under these circumstances provides stronger evidence that the model has learned clinically meaningful relationships rather than characteristics specific to its original training environment.[15,16]

Several sources of heterogeneity can influence transportability of implant-related AI models. Patient demographics may differ between institutions, including age distribution, sex, ethnic background, prevalence of systemic conditions, oral-health status, and patterns of tooth loss.[15,16]

Imaging-related factors represent another important source of variation. CBCT datasets may differ according to scanner manufacturer, field of view, voxel size, exposure parameters, reconstruction algorithms, image resolution, and acquisition protocols. Image quality may also vary because of patient movement, anatomical complexity, restorations, and metallic artifacts. An algorithm developed using images from a particular scanner or standardized acquisition protocol may therefore encounter substantially different input characteristics in another clinical environment.[5,6,15]

The difference between development and deployment data can be conceptualized as dataset shift. Changes may occur in the distribution of patient characteristics, imaging features, predictor variables, or outcome prevalence. Even when the underlying clinical relationship remains similar, a change in the distribution of inputs can alter model performance.[15,16]

External validation in implant-related AI

This imbalance is important because retrospective single-centre studies may provide inflated estimates of performance.[15,16] The same institutional characteristics may influence patient selection, image acquisition, annotation, treatment decisions, and outcome assessment. Consequently, a model can appear highly accurate partly because the development and testing datasets share similar underlying characteristics.[15,16]

External validation helps address this concern by introducing independent sources of variation.[15,16] Nevertheless, even external validation does not automatically establish clinical readiness. A model validated at one additional institution may still perform poorly in other populations or healthcare environments. The strength of evidence therefore increases progressively with broader and more heterogeneous validation.[15,16]

Patient-level heterogeneity is equally important. AI systems should ideally be evaluated across sufficiently diverse patient populations representing the intended clinical use. Factors such as age, sex, anatomical variation, extent of tooth loss, bone morphology, previous implant treatment, restorations, and pathological conditions may influence model performance.[15,16]

Future evaluation of implant-related AI should move beyond isolated reports of high accuracy toward systematic assessment of robustness and transportability. Studies should prospectively define intended population, clinical setting, imaging environment and use case, describe development dataset transparently; perform independent external validation; report calibration and discrimination; evaluate clinically relevant subgroups; and assess whether model provides meaningful clinical benefit.[15,16] Ultimately, the most clinically valuable AI system is not necessarily the model with the highest performance on a single benchmark dataset. Rather, it is the model that maintains reliable performance across diverse patients, imaging systems, institutions, and clinical workflows while providing information that improves clinical decision-making.[15,16]

Explainability and clinical utility

AI systems intended to influence irreversible clinical treatment require transparency. Explainable AI may help clinicians understand which features influenced a recommendation or prediction.

METHODS

This systematic review will follow the PRISMA 2020 statement. The protocol should be prospectively registered in PROSPERO before formal screening where eligible.

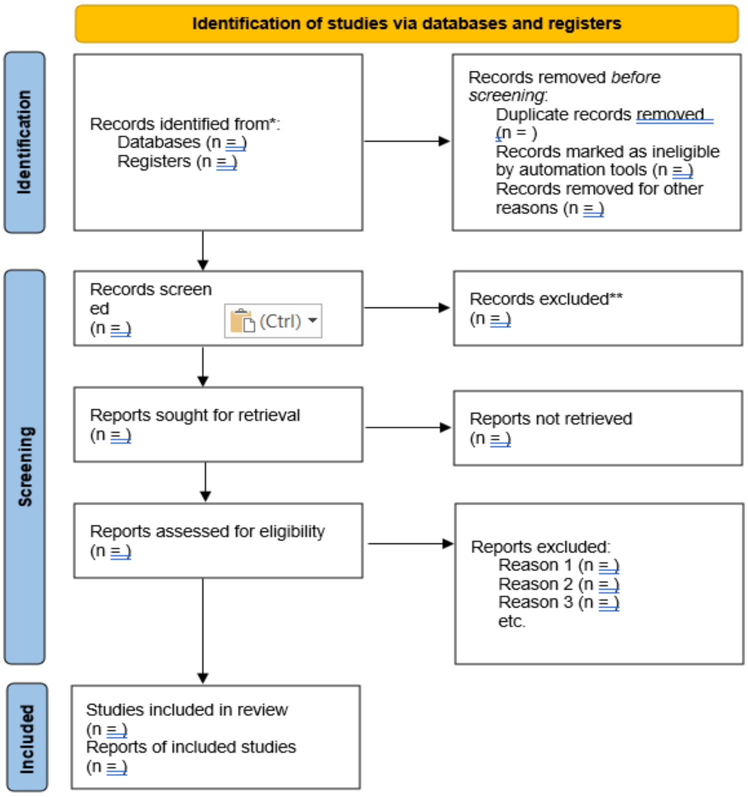

Figure 1: PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only.

*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers); **If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

Table 1: Eligibility criteria for the systematic review.

Domains	Criteria
Population	Human studies involving dental implant diagnosis, planning, or outcome prediction.
Index intervention	AI, machine learning, deep learning, neural networks, or related computational approaches.
Clinical domain	Implant diagnosis, CBCT/anatomical analysis, implant treatment planning, implant positioning, or outcome prediction.
Outcomes	Diagnostic accuracy, segmentation/measurement performance, planning accuracy, implant positioning, implant failure, peri-implant disease, marginal bone loss, osseointegration, implant stability, or other clinically relevant outcomes.
Study designs	Original human studies with quantitative or clinically relevant outcomes.
Exclusions	Animal studies, laboratory-only studies without clinical relevance, editorials, letters, conference abstracts without sufficient data, narrative/systematic reviews, and studies without measurable outcomes.

Table 2: Major AI application domains and intended clinical contribution.

AI domains	Examples of applications	Potential clinical contribution
Diagnosis and image analysis	CBCT interpretation, anatomical segmentation, implant detection, peri-implant bone assessment	Structured anatomical information and reduced repetitive image-analysis tasks.
Treatment planning	Implant-site assessment, bone measurement, implant selection, angulation and depth	More efficient and reproducible virtual planning.

Continued.

AI domains	Examples of applications	Potential clinical contribution
Prosthetically driven planning	Integration of CBCT, intraoral scans, digital wax-ups and restorative design	Alignment of implant position with restorative, biological and aesthetic requirements.
Outcome prediction	Implant failure, peri-implantitis, marginal bone loss, osseointegration and implant stability	Individualized risk assessment and potentially targeted monitoring.
Clinical decision support	Risk stratification and recommendation support	Augmentation of clinician decision-making rather than autonomous treatment

Table 3: Risk-of-bias and reporting assessment framework.

Study type / purposes	Tool	Key domains considered
Diagnostic accuracy	QUADAS-2	Participant selection, index test, reference standard, flow and timing.
Prediction model	PROBAST+AI	Participants, predictors, outcome, analysis, applicability, overfitting and validation.
Prediction-model reporting	TRIPOD+AI	Transparent reporting of development, validation, performance and clinical use.
Prognostic accuracy	QUAPAS, where applicable	Prognostic-study quality and applicability domains as appropriate to study design

Table 4: Core data-extraction domains.

Domains	Variables to be extracted
Study characteristics	Author, year, country/institution, study design, sample size.
Clinical task	Diagnosis, segmentation, planning, positioning, prognosis, or outcome prediction.
AI characteristics	Algorithm/model type, input data, imaging modality, training approach.
Reference standard	Expert assessment, clinical diagnosis, radiographic reference, treatment plan/other defined standard.
Validation	Internal, cross-validation, bootstrap, temporal, external, multicentre, or leave-one-centre-out validation.
Performance	Sensitivity, specificity, accuracy, AUC, overlap measures, calibration, prediction error, or other reported metrics.
Clinical utility	Decision consequences, workflow impact, patient-centered outcomes, cost-effectiveness, or decision-curve analysis where available.

*Databases: PubMed/MEDLINE, Scopus, Web of Science, Embase, and Cochrane Library.

Risk of bias as well as the reporting quality

QUADAS-[2] will be used for diagnostic accuracy studies. QUAPAS may be used for prognostic accuracy studies. PROBAST+AI will be used for artificial intelligence prediction-model studies, while TRIPOD+ Artificial intelligence will be used to evaluate reporting completeness. Important methodological domains include participant selection, predictors, reference standards, outcome definitions, handling of missing data, overfitting, validation strategy, calibration, discrimination, and applicability.

Search concepts: AI, machine learning, deep learning, neural networks, dental implants, implant dentistry, diagnosis, CBCT, segmentation, treatment planning, implant positioning, prognosis, failure, peri-implantitis, marginal bone loss, osseointegration, and implant stability.

Inclusion criteria: human studies involving dental implant diagnosis, planning/soutcome prediction using AI or related machine-learning methods and reporting quantitative or clinically relevant outcomes.

Exclusion criteria: animal studies, laboratory-only studies without clinical relevance, editorials, letters, conference abstracts without sufficient data, narrative reviews, systematic reviews and studies without measurable outcomes.

Two reviewers should independently screen records, assess full texts, and extract data. Disagreements should be resolved by discussion or a third reviewer.

Data synthesis

Studies should be grouped into diagnostic applications, treatment-planning applications, and outcome-prediction applications. Additional synthesis should specifically examine whether models underwent internal validation, temporal validation, external validation, multicentre validation, or leave-one-centre-out validation.

A quantitative meta-analysis should only be performed when studies are sufficiently homogeneous with respect to population, index test, reference standard, outcome, and performance metric. Otherwise, findings should be synthesized narratively.

DISCUSSION

AI has considerable potential to support implant dentistry across the complete treatment pathway. Image-based applications currently provide some of the strongest evidence, particularly anatomical segmentation and CBCT analysis. Treatment-planning systems are also developing rapidly, including prosthetically driven implant positioning.

However, clinical adoption requires more than high accuracy on a development dataset. The quality of the training data, representativeness of the population, reference standards, model calibration, external validation, interpretability, and clinical workflow integration all influence the reliability of AI.

The literature therefore supports cautious optimism. AI can potentially improve efficiency and consistency, but clinician oversight remains essential. Future investigations should focus on prospective multicentre validation, standardized outcomes, external testing, explainability, decision-curve analysis, cost-effectiveness, and patient-centered outcomes.

Limitations of the current evidence

The existing evidence is limited by retrospective study designs, relatively small or institution-specific datasets, inconsistent outcome definitions, heterogeneous AI architectures, differences in performance metrics, limited external validation, and relatively sparse evidence regarding patient-centered outcomes.

Rapid technological development also creates the possibility that algorithms evaluated today may become outdated as imaging protocols, software platforms, and AI architectures evolve.

CONCLUSION

Artificial intelligence is rapidly transforming digital implant dentistry. Current evidence demonstrates promising applications in diagnosis, anatomical segmentation, implant treatment planning, prosthetically driven implant positioning, and prediction of implant-related outcomes.

The major challenge is now clinical translation. Future studies should prioritize prospective multicentre validation, external validation, calibration, explainability, standardized datasets, transparent reporting, clinical utility, cost-effectiveness, and patient-centered outcomes. At present, AI should be regarded as a clinical decision-support technology that augments, rather than replaces, the expertise and judgment of the implant clinician.

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