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BRIEF COMMUNICATION

Artificial intelligence in implant dentistry: diagnostic performance, prediction, and design optimization

La inteligencia artificial en la implantología dental: rendimiento diagnóstico, predicción y optimización del diseño

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ABSTRACT

Artificial intelligence has emerged as a valuable tool in dental implantology, with applications focused on implant type recognition, the prediction of clinical success, and design optimization through integration with biomechanical models. Systems based on machine learning and deep learning enable the analysis of radiographic images and clinical variables to generate results that support decision-making. In the case of implant type recognition, the accuracy levels of the evaluated models ranged between 93,8 % and 98 %, suggesting high potential for classification tasks under controlled conditions. However, this accuracy is limited by the use of restricted datasets, given that more than 2,000 types of implants are available on the market. In predicting implant success, the results were more variable, with values ranging from 62,4 % to 80,5 %, reflecting the biological and clinical complexity of this type of prognosis. In terms of design, the combination of artificial intelligence with finite element analysis resulted in improvements, such as a 36,6 % reduction in stress at the implant–bone interface, although these results are based on computational models without direct clinical validation. At the methodological level, relevant limitations were identified, including heterogeneity in outcome measures, lack of clarity in eligibility criteria, and a high risk of bias in some of the analyzed studies. Overall, the evidence suggests that artificial intelligence has significant potential in dental implantology, although its clinical application still requires further validation and methodological standardization.

Keywords: Artificial Intelligence; Dental Implantology; Machine Learning; Prediction of Implant Success; Implant Design; Diagnostic Imaging; Finite Element Analysis.

RESUMEN

La inteligencia artificial ha emergido como una herramienta relevante en la implantología dental, con aplicaciones orientadas al reconocimiento del tipo de implante, la predicción del éxito clínico y la optimización del diseño mediante integración con modelos biomecánicos. Los sistemas basados en aprendizaje automático y aprendizaje profundo permiten analizar imágenes radiográficas y variables clínicas para generar resultados que apoyan la toma de decisiones. En el caso del reconocimiento del tipo de implante, los modelos evaluados alcanzaron niveles de exactitud entre 93,8 % y 98 %, lo que sugiere un alto potencial en tareas de clasificación bajo condiciones controladas. Sin embargo, esta precisión está limitada por el uso de conjuntos de datos restringidos, considerando que existen más de 2000 tipos de implantes en el mercado. En la predicción del éxito del implante, los resultados fueron más variables, con valores entre 62,4 % y 80,5 %, lo que refleja la complejidad biológica y clínica de este tipo de pronóstico. En cuanto al diseño, la combinación de inteligencia artificial con análisis de elementos finitos permitió mejoras como la reducción del estrés en la interfaz implante-hueso en un 36,6 %, aunque estos resultados se basan en modelos computacionales sin validación clínica directa. A nivel metodológico, se identificaron limitaciones relevantes, incluyendo heterogeneidad en los indicadores de resultado, falta de claridad en los criterios de elegibilidad y alto riesgo de sesgo en parte de los estudios analizados. En conjunto, la evidencia sugiere que la inteligencia artificial tiene un potencial significativo en implantología dental, aunque su aplicación clínica aún requiere validación adicional y estandarización metodológica.

Palabras clave: Inteligencia Artificial; Implantología Dental; Aprendizaje Automático; Predicción del Éxito del Implante; Diseño de Implantes; Diagnóstico por Imagen; Análisis de Elementos Finitos.

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BACKGROUND

Artificial intelligence in implant dentistry can be framed as a computational approach aimed at intelligent system behavior, in which algorithms learn patterns from data to support future decision-making. Within this broader concept, machine learning is presented as a subgroup in which models learn statistical patterns from a dataset to predict future data samples,[1] whereas deep learning is described as a class of machine learning that uses three or more neural network layers with weighted inputs and biases to emulate neuron-like processing.[2] In medical contexts, the summary distinguishes virtual applications, such as electronic health records and diagnostic or treatment planning software, from physical applications, such as robot surgical aids and smart prostheses.[3] In dentistry and implantology, the reported systematic review frames AI as an expanding area of investigation that addresses both recognition tasks and planning-oriented tasks, including design optimization that integrates mechanical modeling outputs with AI-derived components.[2,4,5]

The most direct diagnostic element of the evidence concerns recognition of the implant type from imaging. Seven included studies used periapical and panoramic radiographs, and the reported overall accuracy for implant type detection ranged from 93,8 % to 98 %. This narrow accuracy band indicates that, under the conditions represented in those primary studies, image-based classifiers reached performance levels close to the upper bound typically associated with image categorization tasks. The recognition models were constructed using classical machine learning algorithms, including decision tree learning, random forest, logistic regression, and multidimensional unfolding analysis, as well as artificial neural network approaches such as deep convolutional neural networks and residual neural networks. The presence of both classical and deep architecture suggests that high accuracy may be achievable using distinct feature-learning strategies; however, the summary also reports that implant-type recognition models were tested on a limited set of dental implant systems and that more than 2000 implant types exist on the market. Accordingly, the upper accuracy range should be interpreted as conditional on the implant systems represented in the training and evaluation data rather than as evidence of universal generalization to the full commercial landscape.

A second major domain concerns predictive modeling of implant success, where prognosis is inferred from patient risk factors and ontology criteria. Seven studies summarized osteointegration or implant success forecasts, with reported accuracies ranging from 62,4 % to 80,5 %. Relative to the recognition accuracy range, the broader and lower performance span reflects differences in task structure and outcome observability. Implant success prediction depends not only on image-based features but also on patient characteristics and risk criteria that may be related to complex biological and clinical processes. The summary identifies heterogeneity of the indexes for the presentation of results as a key flaw in primary study reporting. This implies that accuracy variability may stem from differences in success definitions, feature sets, patient populations, and modeling targets, and since no single shared reference standard is specified across all primary studies, the interpretation of prognostic performance must account for the likelihood that success was operationalized differently across datasets.

Design optimization represents a third application category that combines AI modeling with finite element analysis. Three studies were included in this domain. In summary, compared with the FEA model, the AI model reduced stress at the implant–bone interface by 36,6 %. The design work also included optimization of the implant porosity, length, and diameter; improvements in FEA calculations; and accurate determination of the elastic modulus of the implant–bone interface. These results suggest that AI may serve as a surrogate or augmentation layer that modifies or refines mechanical modeling outputs, potentially improving stress distribution predictions or selecting design parameters within the simulated biomechanical space. However, the summary frames these mechanical improvements as part of model-based optimization without reporting clinical validation. Stress reduction and parameter optimization should therefore be interpreted as computational indicators rather than direct evidence of improved patient outcomes.

Methodological limitations at the systematic review level constrain how strongly the quantitative results can be interpreted. The summary reports for which gray literature was not mentioned were included, a gap described as relevant to digital health research and associated with publication bias risk. The protocol was not registered at PROSPERO,[6] which affects transparency and bias control. For diagnostic accuracy questions, the summary indicates that reporting of PICO elements was unclear and that PIRD would be more appropriate.[7] It further reports the use of a JBI Critical Appraisal Checklist for Quasi-Experimental Evaluation, while it notes that QUADAS-2 is recommended for diagnostic accuracy studies per JBI.[7] Among the 17 included studies, 9 were low-risk studies, and 8 were high-risk studies, indicating that approximately half of the evidence base had limitations that may influence the reported performance estimates.

At the level of primary study reporting, key flaws were identified as diversity of indexes for result presentation, unclear eligibility criteria, and inadequate descriptions of the reference test. These issues affect duplication and reproducibility, as linked to the STARD criteria.[8] The recognition models were tested on a limited subset of dental implant systems, whereas the commercial market contains more than 2000 types, implying that observed performance cannot be assumed to transfer to unrepresented systems. This summary characterizes clinical application as early-stage and calls for combining AI technology with traditional methods to reduce output errors, indicating that AI outputs should be treated as decision support rather than stand-alone determinations, particularly for tasks where misinterpretation could affect prosthetic selection or planning.

Risks and interpretive limitations are explicitly described as integral to AI deployment. In summary, AI reflects associations rather than causality, which is important for clinical reasoning because prognosis and success depend on mechanisms that may not be fully captured by observational correlations. It also states that AI cannot provide direct interpretation, raising the possibility that algorithmic misconduct or misinterpretation could produce clinically misleading outputs. The summary argues for comprehensive multiapplication architectures combined with clinician oversight and emphasizes interprofessional collaboration between clinicians and computer engineers as essential for reducing such risks.

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Future research directions in the summary align with both methodological standardization and practical evaluation. Adherence to emerging AI reporting guidelines, including STARD-AI,[9] SPIRIT-AI,[10] CONSORT-AI,[11] TRIPOD, EQUATOR, and the dental AI checklist,[4] is recommended. Protocol registration at PROSPERO[6] would address transparency concerns, and QUADAS-2 adoption[7] would align appraisal with recommended standards for diagnostic accuracy. On the empirical side, broader datasets across implant systems are needed to improve generalizability. The summary also calls for the integration of AI with conventional workflows and continued interprofessional collaboration. Given that design optimization findings include stress reduction and parameter selection without clinical validation, further work is needed to connect optimization outputs to patient-relevant endpoints while maintaining transparent reporting of reference tests, eligibility criteria, and outcome definitions across study populations.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

AUTHORSHIP CONTRIBUTIONS

Conceptualization: Jadier Wong Silva, Maria Isabel Brusca.
Writing – original draft: Jadier Wong Silva, Maria Isabel Brusca.
Writing – review and editing: Jadier Wong Silva, Maria Isabel Brusca.

REFERENCES

1. Alpaydin E. Introduction to Machine Learning. MIT Press; 2020.

2. Corbella S, Srinivas S, Cabitza F. Applications of deep learning in dentistry. Oral Surg Oral Med Oral Pathol Oral Radiol. 2021;132(2):225-238.

3. Holmes J, Sacchi L, Bellazzi R. Artificial intelligence in medicine. Ann R Coll Surg Engl. 2004;86:334-338.

4. Schwendicke F, Singh T, Lee JH, et al. Artificial intelligence in dental research: Checklist for authors, reviewers, readers. J Dent. 2021;107:103610.

5. Al-Sarem M, Al-Asali M, Alqutaibi AY, Saeed F. Enhanced tooth region detection using pretrained deep learning models. Int J Environ Res Public Health. 2022;19(22).

6. Pieper D, Rombey T. Where to prospectively register a systematic review. Syst Rev. 2022;11(1):1-8.

7. Campbell JM, et al. Diagnostic test accuracy: methods for systematic review and meta-analysis. JBI Evidence Implementation. 2015;13(3):154-162.

8. Cohen JF, et al. STARD 2015 guidelines for reporting diagnostic accuracy studies: explanation and elaboration. BMJ Open. 2016;6(11):e012799.

9. Sounderajah V, et al. Developing specific reporting guidelines for diagnostic accuracy studies assessing AI interventions: the STARD-AI Steering Group. Nat Med. 2020;26(6):807-808.

10. Rivera SC, et al. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. Lancet Digit Health. 2020;2(10):e549-e560.

11. Liu X, et al. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. BMJ. 2020;370.