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Review

Artificial intelligence models and predicting implant success

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ABSTRACT

The integration of artificial intelligence (AI) into dental implantology has revolutionized the field, offering enhanced predictive capabilities that empower clinicians to optimize treatment outcomes. By leveraging AI, dental professionals can analyze vast amounts of patient data with unprecedented accuracy and efficiency. This advancement not only improves patient outcomes but also reduces healthcare costs by minimizing complications and streamlining treatment planning. Furthermore, AI paves the way for more personalized and successful patient care. Despite these promising developments, significant research gaps remain. These include understanding how to optimally integrate AI with diverse clinical datasets and addressing variability in patient responses. The integration of AI into dental implantology enhances not only the precision and efficiency of treatment planning and execution but also enables a more tailored approach to patient care. This review explores the potential of machine learning approaches in predicting the success of dental implant procedures. Additionally, it highlights the benefits of combining AI-generated predictions with patient-specific factors, such as bone quality, implant location, and overall health status. By adopting this holistic approach, clinicians can achieve a more accurate and personalized assessment of implant success probability, ultimately improving treatment planning and long-term outcomes.

Key words: Artificial Intelligence, Dental Implants, Treatment Outcome

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INTRODUCTION

Every year, millions of people undergo dental implant procedures, with studies showing that nearly 70% of adults aged 35 to 44 have lost at least one permanent tooth. The success of these implants depends on various factors that significantly influence patient outcomes, underscoring the importance of clinicians accurately predicting the likelihood of successful integration [1,2]. Dental implants have emerged as a widely accepted and reliable solution for replacing missing teeth, offering enhanced function, aesthetics, and long-term oral health benefits for patients [1]. The success of dental implants—defined by their ability to integrate with surrounding bone and support functional restorations—is critically important to both clinicians and patients. Accurately predicting the likelihood of implant success is essential for effective treatment planning, patient selection, and managing expectations [2].

Traditional methods for predicting implant success, such as clinical assessments, radiographic evaluations, and consideration of patient-specific factors, have shown limited predictive accuracy [3]. Factors like bone quality, implant design, surgical technique, and patient characteristics can all influence implant outcomes, making it difficult to reliably forecast success using conventional approaches [4]. In recent years, artificial intelligence (AI) has emerged as a promising tool for improving the prediction of dental implant success. AI-based models, which leverage advanced machine learning algorithms, have the potential to analyze complex datasets, identify subtle patterns, and generate more accurate predictions compared to traditional methods [5]. By integrating patient-specific clinical data, radiographic information, and other relevant variables, AI-powered systems may offer clinicians a more comprehensive and reliable means of assessing the likelihood of successful implant integration and long-term functionality [6].

This review paper aims to explore the current state of research on the application of AI models for predicting dental implant success. It will examine various machine learning approaches, including regression models, decision trees, and neural networks, and their potential to enhance the accuracy of implant success predictions. Additionally, the paper will discuss the integration of AI models with clinical data, the challenges associated with their implementation, and future directions in this rapidly evolving field.

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MACHINE LEARNING APPROACHES FOR IMPLANT SUCCESS PREDICTION

Machine learning has emerged as a promising approach for enhancing the prediction of dental implant success. By leveraging advanced algorithms and data-driven models, researchers have explored various machine learning methodologies to improve the accuracy of implant outcome forecasting[7]. The increased use of machine learning in dentistry is driven by the growing availability of large datasets and the need for more accurate and personalized treatment planning. Traditional statistical methods have limitations in handling the complex, multifactorial nature of dental implant outcomes. Machine learning models, on the other hand, can identify and learn from intricate patterns within large datasets, allowing for more precise predictions of implant success and failure[3,4]. These models can incorporate a wide range of variables, including demographic, clinical, radiographic, and genetic data. The application of machine learning in implant dentistry has been explored across various domains, such as implant survival prediction, implant failure risk assessment, implant treatment planning optimization, and peri-implant tissue health monitoring[8,9]. These advances hold the potential to improve clinical decision-making, enhance patient outcomes, and reduce the burden of implant-related complications.

One of the fundamental machine learning approaches applied in the context of implant success prediction is regression analysis. Regression models aim to establish a mathematical relationship between a set of independent variables and a dependent variable, thereby enabling the forecasting of future outcomes[10]. Several types of regression models (as shown in Table 1) have been explored in implant success prediction, showing promise in improving the accuracy of implant success prediction and enabling clinicians to make more informed decisions[11,12].

Logistic regression is a widely used statistical modeling technique that predicts the probability of a binary or categorical outcome variable based on one or more predictor variables. The model utilizes the logistic function to transform the linear combination of predictors into a probability value between 0 and 1. Logistic regression has emerged as a valuable technique in dental implant research, enabling the identification of key factors that influence implant success or failure[17]. Implant success is typically defined by long-term retention, functionality, stability, absence of complications, and patient satisfaction. Researchers have used logistic regression to investigate patient-, implant-, and procedure-related factors that can influence the probability of successful outcomes. These factors include patient characteristics, implant features, and surgical/prosthetic factors. The model's output provides odds ratios for each predictor variable, representing the change in the odds of implant success associated with a unit change in the corresponding variable. This information can help clinicians identify high-risk patients, guide treatment planning, and inform patients about potential risks and expected outcomes. The insights from logistic regression models have practical applications in patient selection, treatment planning, informed consent, quality improvement, and research collaboration[18].

The Cox Proportional Hazards (Cox PH) regression model is a powerful statistical tool in dental implantology, where understanding the factors contributing to long-term implant success is crucial. Unlike logistic regression, which focuses on binary outcomes, the Cox PH model is a survival analysis technique that examines the time to implant failure. It assesses the influence of multiple predictor variables on the hazard (risk) of implant failure over time, under the assumption of proportional hazards. The Cox PH model has been widely adopted in dental implant research to address various questions, such as identifying risk factors, comparing survival rates, predicting implant survival, evaluating time-dependent covariates, and exploring potential interactions between predictors[19]. This enables researchers and clinicians to gain a more comprehensive understanding of the factors impacting long-term implant performance. The Cox PH model offers advantages like handling censored data and incorporating both time-dependent and time-independent covariates[20]. However, it assumes proportional hazards, which may not always hold true. In such cases, researchers may need to employ alternative survival analysis methods or modify the Cox PH model to address violations of the proportional hazards assumption. When used in conjunction with logistic regression, the Cox PH regression model can provide a holistic view of the factors impacting the long-term success of dental implants, ultimately leading to improved patient care and outcomes[21].

DECISION TREE MODELS

Decision tree models have become an invaluable tool in dental implant research, offering a structured approach to identifying key factors that influence the success or failure of dental implants. Unlike traditional regression-based methods, decision tree models utilize a hierarchical, tree-like structure to visually represent the decision-making process. This

Table 1: Regression-based Machine Learning Models Explored for Predicting Dental Implant Success

Regression models		Ref.
Linear Regression	This approach aims to find the linear relationship between the independent variables (*e.g.*, patient age, bone density, implant dimensions) and the dependent variable (*e.g.*, implant survival time). Linear regression models provide a straightforward way to quantify the influence of each factor on the expected implant outcome.	13
Logistic Regression	When the dependent variable is binary (*e.g.*, implant success or failure), logistic regression is commonly used to model the probability of a specific outcome occurrence. This method helps identify the risk factors associated with implant failure and can be used to classify patients into high-risk or low-risk groups.	14
Cox Proportional Hazards Regression	This time-to-event analysis technique is particularly useful for predicting the survival of dental implants over time. It allows the incorporation of censored data, where the exact time of implant failure is unknown, and provides hazard ratios to quantify the impact of each predictor variable on the risk of implant failure.	15
Multivariate Regression	To capture the complex, multifactorial nature of implant outcomes, researchers have explored the use of multivariate regression models that incorporate multiple independent variables simultaneously. These models can provide a more comprehensive understanding of the factors influencing implant success.	16

visual representation enhances interpretability, enabling clinicians and researchers to better understand the complex relationships between predictor variables and outcomes[7,22].

The decision tree algorithm operates by recursively partitioning the dataset into increasingly homogeneous subgroups based on predictor variables. At each decision node, the model evaluates the available variables and selects the one that maximizes information gain or minimizes impurity measures, such as Gini impurity or entropy, to split the data[11,23]. This process continues iteratively until a terminal node is reached, where the model assigns a predicted outcome based on the majority class or the average value of the target variable within that subgroup[24].

One of the primary strengths of decision tree models lies in their versatility. They can handle both categorical and continuous variables, making them particularly well-suited for analyzing the multifactorial and complex nature of dental implant outcomes[7,25]. Furthermore, decision tree models excel at capturing non-linear relationships and interactions among predictor variables, which are often overlooked by traditional linear models[26].

In dental implant research, decision tree models have been widely applied to predict various outcomes, including implant survival, peri-implant bone loss, and complications. These models have been instrumental in examining the impact of patient-related factors—such as age, gender, and smoking status—as well as implant-related factors—such as surface characteristics, diameter, and length—on the long-term success of dental implants[27].

The interpretability of decision tree models also makes them a powerful tool for clinical decision-making. By providing a clear and intuitive visualization of the decision-making process, these models help clinicians identify the key factors contributing to implant success and develop personalized treatment strategies[22,28]. This enhanced understanding enables clinicians to make more informed decisions, ultimately improving patient outcomes[29].

Despite their advantages, decision tree models are not without limitations. A common challenge is overfitting, where the model becomes overly complex and captures noise rather than the underlying patterns in the data. This can result in poor generalization to new, unseen data. To address this issue, techniques such as pruning—removing branches with limited significance—can be employed. Additionally, setting constraints such as a maximum tree depth or a minimum number of samples required at a leaf node can help create a more robust model that balances complexity and accuracy. Regularization methods and cross-validation can further ensure that the model maintains predictive power while minimizing the risk of overfitting (**Figure 1**).

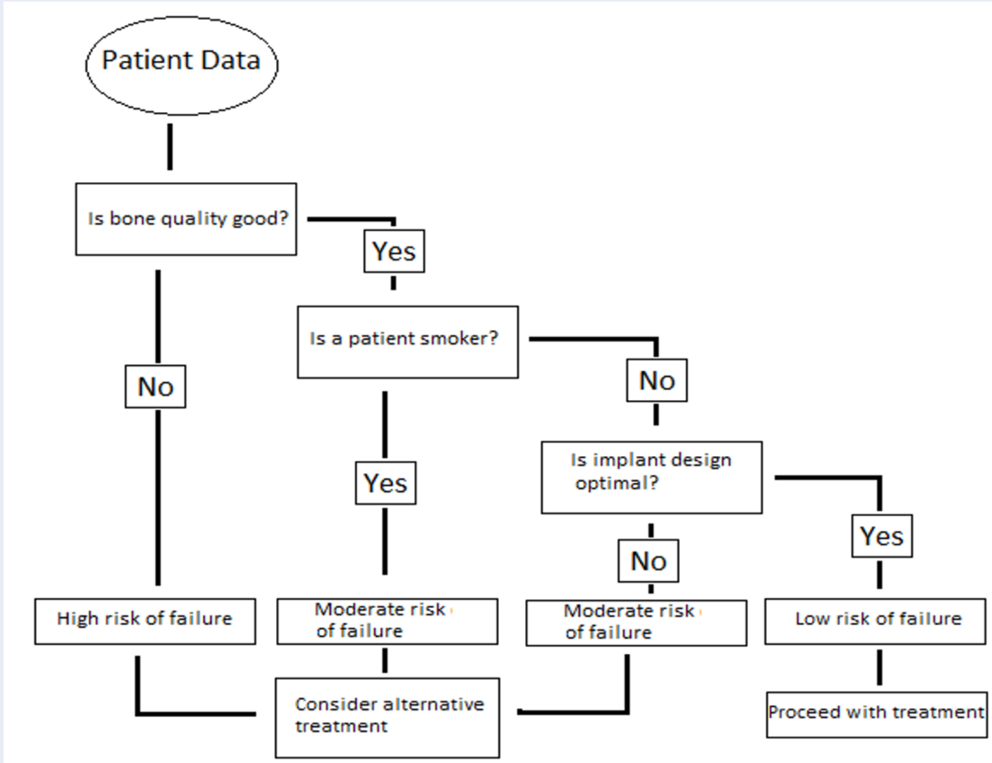

Figure 1: **Flowcharts of decision trees for dental implant risk assessment**. The decision tree model evaluates the risk of failure in dental implant treatments utilizing patient data. The process initiates with bone quality assessment as the primary decision node. Inadequate bone quality indicates a high risk of failure, suggesting the need for alternative treatments. If bone quality is adequate, the model proceeds to assess smoking status. Smoking is further evaluated for its impact on treatment outcomes, followed by an assessment of implant design considerations. The decision tree concludes with risk classifications: moderate risk of failure if implant design is suboptimal, and low risk if all parameters are favorable. This structured methodology aids in identifying key factors impacting implant success and assists clinicians in making informed, patient-specific treatment decisions.

NEURAL NETWORK MODELS IN DENTAL IMPLANT RESEARCH

The application of artificial neural networks (ANNs) has emerged as a powerful tool in dental implant research, offering significant potential for predicting implant success and identifying key influencing factors[30,31]. Neural network models, a class of machine learning algorithms inspired by the structure and function of the human brain, excel at learning complex, non-linear relationships from large datasets[32]. In dental implantology, these models have been employed to predict a range of outcomes, including implant survival, peri-implant bone loss, and the likelihood of complications[33]. Their ability to handle the multifactorial nature of implant success—encompassing patient-related, implant-related, and surgical factors—makes them particularly well-suited for this domain[22,34].

The training process for neural network models typically involves inputting extensive datasets comprising patient and implant characteristics alongside corresponding outcomes. The model learns the underlying patterns and relationships, which it then applies to make predictions on new, unseen data. This capability provides clinicians with valuable insights into the factors most critical to implant success[11,34]. A key advantage of neural networks lies in their ability to identify complex, non-linear relationships that traditional statistical methods, such as logistic regression, often fail to capture[11]. Furthermore, their capacity to process both categorical and continuous variables makes them highly adaptable to the diverse range of factors influencing dental implant outcomes[11,35].

Among the most widely used neural network architectures is the Multi-layer Perceptron (MLP), which consists of an input layer, one or more hidden layers, and an output layer. This structure enables the model

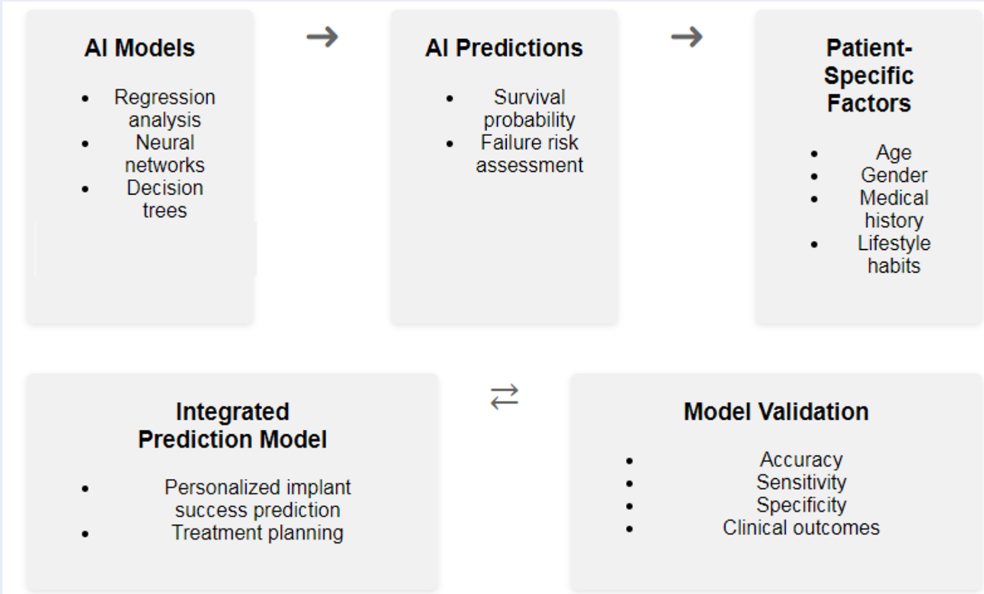

Figure 2: **Integrated approach to personalized implant success prediction**. This figure demonstrates a comprehensive strategy for integrating artificial intelligence (AI) models with patient-specific factors to improve dental implant success prediction. Initially, various AI models—such as regression analysis, neural networks, and decision trees—analyze complex patient data to generate vital predictions about implant survival probabilities and failure risks. These predictions are refined by including patient-specific factors like age, gender, medical history, and lifestyle habits. The resulting integrated prediction model aids in providing personalized implant success predictions and customized treatment plans. Finally, the model undergoes a validation phase to evaluate its accuracy, sensitivity, specificity, and overall clinical outcomes, highlighting its potential to enhance decision-making and improve long-term success in dental implant treatments.

to learn intricate, non-linear relationships between input variables and target outputs, such as implant survival or peri-implant bone loss[35]. Another notable architecture is the Radial Basis Function (RBF) Network, which utilizes radial basis functions as activation functions in the hidden layer. This design is particularly effective for modeling highly non-linear relationships and delivering accurate predictions with fewer neurons, making it a valuable tool for classifying complex patterns in dental implant data[36].

Convolutional Neural Networks (CNNs) have also been applied to process grid-like data, such as dental images or radiographic data. CNNs enable the automatic extraction of features from raw imaging information, which can then be used to predict implant outcomes[22,37]. For sequential data, such as time-series information related to implant performance over time, Recurrent Neural Networks (RNNs) have proven effective in capturing temporal dependencies and dynamics[38]. Additionally, ensemble methods—which combine multiple neural network models or other machine learning algorithms—have been employed to enhance predictive performance in dental implant research[11,39]. The selection of a specific neural network model depends on the nature of the data, the complexity of the problem, and the desired balance between interpretability and accuracy. As research progresses, these advanced computational techniques continue to demonstrate their potential to improve the understanding and management of dental implant success.

MLPs and CNNs, in particular, have shown remarkable efficacy in learning complex, non-linear relationships between clinical parameters and implant-related outcomes[40,41]. These models are trained on large, meticulously curated datasets that encompass a wide range of patient demographics, medical histories, implant characteristics, and clinical measurements, such as peri-implant bone levels and soft tissue health. By leveraging the pattern recognition and generalization capabilities of neural networks, researchers have developed predictive models that outperform traditional statistical approaches, which often struggle to account for the intricate interplay of factors influencing implant success[41].

The integration of clinical data with other relevant information—such as imaging data (*e.g.*, radiographs, CBCT scans) and genetic markers—has further enhanced the predictive power of these AI-driven systems[42,43]. A notable application of this integration is the prediction of peri-implant bone loss, a critical indicator of long-term implant survival. By training neural networks on longitudinal data, including patient-specific characteristics, implant design features, and radiographic assessments, researchers have developed models capable of accurately forecasting the progression of peri-implant bone loss. This capability enables early intervention and personalized treatment planning[39]. Moreover, the combination of AI models and clinical data has shown promise in identifying the most influential factors contributing to implant success, such as patient age, smoking status, oral hygiene, and bone density[44,45]. These insights can inform clinical decision-making, patient selection, and the optimization of treatment protocols, ultimately leading to improved long-term outcomes and reduced complications.

The integration of AI models with clinical data represents a significant advancement in dental implantology, offering transformative potential for the field. However, neural networks are not without limitations. They require large datasets for effective training, as insufficient data can lead to poor generalization on unseen cases. Additionally, these models are susceptible to overfitting, where they learn noise in the training data rather than underlying patterns, which can compromise their performance on new data. Techniques such as regularization, dropout, and cross-validation can mitigate these issues, but their implementation requires careful consideration. As the field evolves, further research is needed to refine and validate the use of these advanced computational techniques in predicting and managing dental implant success[22,39].

INTEGRATING AI PREDICTIONS WITH PATIENT-SPECIFIC FACTORS IN DENTAL IMPLANTOLOGY

The successful osseointegration of dental implants is a multifactorial process influenced by a wide range of patient-specific and implant-related variables[46]. As the demand for dental implants continues to rise, clinicians are increasingly seeking advanced tools and strategies to enhance treatment predictability, reduce complications such as peri-implant bone loss, infection, and implant failure, and improve long-term outcomes[47]. Recent advancements in machine learning have enabled the development of predictive models capable of analyzing complex patient data to identify critical factors influencing implant success[11].

A key advantage of AI in this domain lies in its ability to process and integrate diverse patient-specific variables, including demographic data, medical history, oral health status, implant specifications, and radiographic findings[44]. Unlike traditional statistical methods, which often struggle to capture the intricate relationships among these multidimensional factors, AI models excel at uncovering subtle patterns and interactions that may elude human clinicians[11]. For instance, one study demonstrated the use of an AI model to determine the optimal implant size, angle, and position based on individual anatomical features, bone density, and other clinical parameters[48]. By integrating this AI-driven planning tool with patient-specific data, researchers achieved greater precision in implant placement and reduced the risk of complications.

Similarly, another study employed a multilayer perceptron (MLP) neural network to combine patient demographics, medical history, and implant-specific data, enabling accurate predictions of long-term implant survival rates[33]. This predictive capability allows clinicians to assess individual patient prognoses more effectively and make evidence-based decisions regarding treatment options[33]. Furthermore, AI models have proven adept at identifying key risk factors for implant failure, such as smoking status, poor bone density, and systemic diseases[5]. By incorporating these risk profiles into clinical assessments, clinicians can implement targeted interventions and closely monitor high-risk patients, thereby improving overall treatment outcomes[5,33,48].

In another innovative application, researchers developed a machine learning model that integrated patient-specific factors—such as age, gender, and oral hygiene habits—with implant-related variables, including surface characteristics and placement protocols. This model accurately predicted the risk of peri-implant bone loss, a common complication associated with dental implants[39,43,49]. By incorporating such predictive tools into clinical practice, dentists can identify high-risk patients early and implement preventive strategies to mitigate the risk of implant failure[39]. This approach enables clinicians to optimize patient selection and tailor treatment plans to individual needs, ultimately enhancing the long-term success of dental implants.

In summary, the integration of AI-driven predictive models with comprehensive patient-specific data holds significant potential to transform the field of dental implantology. By leveraging machine learning algorithms to analyze complex, multifactorial datasets, clinicians can make more informed decisions, refine treatment planning, and improve the long-term success rates of dental implants for their patients (**Figure 2**).

CHALLENGES AND FUTURE DIRECTIONS

Integrating AI models with dental implant data has shown promising results in enhancing the predictability of treatment outcomes, but several challenges and future directions need to be addressed in this rapidly evolving field. One of the primary challenges is the heterogeneity and lack of standardization in the clinical data used to train AI models, as disparities in data collection methods, patient populations, and reporting practices can introduce biases and limit the generalizability of the developed models [44,50,51]. To overcome this, efforts are needed to establish standardized data collection protocols, shared data repositories, and collaborative research initiatives that can facilitate the aggregation of high-quality, representative datasets [52].

As AI models become more complex, the need for interpretability and explainability becomes increasingly important, especially in the context of clinical decision-making [53]. Researchers and clinicians should strive to develop AI models that can provide transparent and explainable insights into the factors driving the prediction of implant success or failure, which will help build trust and facilitate the integration of these tools into clinical practice.

The ultimate goal of AI-powered predictive models is to provide real-time, personalized recommendations during the treatment planning and implant placement process, which will require the development of seamless integration with clinical workflows, electronic health records, and intraoperative data acquisition systems [54]. Robust longitudinal studies are necessary to validate the long-term performance and clinical utility of AI-based predictive models in dental implantology, as continuous monitoring of patient outcomes—including implant survival rates, peri-implant health, and patient-reported satisfaction—will help refine and improve the accuracy of these models over time [54].

As the use of AI in healthcare becomes more widespread, it is essential to address the ethical implications, such as data privacy, bias, and transparency, to ensure the responsible and equitable deployment of these technologies. Regulatory bodies should establish clear guidelines and validation frameworks to ensure the safety, efficacy, and ethical use of AI-powered predictive tools in the dental implant industry [55].

Successful implementation of AI-based predictive models in dental implantology will require close collaboration among clinicians, radiologists, data scientists, and biomedical engineers, as fostering interdisciplinary teams and facilitating knowledge exchange will be crucial for driving innovation and translating research findings into practical clinical applications. Furthermore, ongoing advancements in imaging technologies, such as high-resolution CBCT, intraoral scanning, and emerging modalities like augmented reality, will provide increasingly detailed and accurate data for integration with AI models, while improvements in machine learning algorithms, computational power, and data processing capabilities will enhance the predictive performance and real-time capabilities of these models [11].

Looking ahead, the future of AI in dental implantology is promising, with several key areas for research and clinical application. First, the development of hybrid models that combine AI with traditional clinical expertise could enhance decision-making processes. Second, expanding the datasets used for training AI models to include diverse populations will improve the generalizability and applicability of these tools across different demographics. Third, researchers should focus on integrating AI with emerging technologies, such as augmented reality and virtual simulations, to create interactive platforms for training and planning. Finally, fostering interdisciplinary collaborations among clinicians, data scientists, and engineers will be crucial for driving innovation and translating research findings into practical applications. By addressing these areas, the dental implant field can leverage AI to improve patient outcomes and streamline clinical workflows.

CONCLUSION

The integration of artificial intelligence (AI) models into dental implantology has heralded a transformative shift, offering unprecedented advancements in precision, efficiency, and predictive accuracy. This innovative technology addresses critical challenges encountered by clinicians during implant identification, treatment planning, and outcome prediction. A key advantage of AI lies in its capacity to predict the likelihood of successful osseointegration and identify potential risk factors associated with implant failure. By serving as a robust decision-support tool, AI enables clinicians to make evidence-based decisions, thereby improving the overall success rates of dental implant therapies. Additionally, AI has demonstrated remarkable efficacy in the early detection of peri-implantitis, a significant concern for the long-term maintenance of dental implants. Nevertheless, despite its considerable promise, the clinical application of AI is not without limitations. Ongoing research and rigorous clinical validation are imperative to ensure the reliability and generalizability of AI models in real-world dental practice. Furthermore, the development of well-curated datasets and advanced AI architectures remains essential, as these foundational components are critical to the successful implementation of AI in dental implantology.

ABBREVIATIONS

AI - Artificial Intelligence, **CBCT** - Cone Beam Computed Tomography, **CNN** - Convolutional Neural Network, **Cox PH** - Cox Proportional Hazards, **MLP** - Multi-layer Perceptron, **RBF** - Radial Basis Function, **RNN** - Recurrent Neural Network

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AUTHOR'S CONTRIBUTIONS

Yasin Nazari: Conceptualized the review, gathered relevant literature, and drafted the initial manuscript. **Parsa Farhadian Langeroodi**: Conducted a comprehensive literature search, contributed to the synthesis of findings, and provided critical revisions. **Moein Maddahi**: Assisted in organizing the structure of the review, analyzed key themes, and contributed to the writing process. **Sepehr Kobravi**: Reviewed and summarized specific studies, ensuring the integration of diverse perspectives within the narrative. **Mahmood Rezvani Amin**: Contributed expertise on AI applications in dental implantology, enhancing the discussion on predictive models. **Amir Abdollah Bargrizaneh**: Participated in the literature review, focused on patient-specific factors, and assisted in refining the manuscript. **Saman Fouladi**: Conceptualized the review, Provided editorial support, coordinated contributions among authors, and ensured compliance with journal guidelines. All authors read and approved the final manuscript.

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The authors declare that they have no competing interests.

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