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SYSTEMATIC REVIEW

Artificial intelligence applications in implant dentistry: A systematic review

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ABSTRACT

Statement of problem. Artificial intelligence (AI) applications are growing in dental implant procedures. The current expansion and performance of AI models in implant dentistry applications have not yet been systematically documented and analyzed.

Purpose. The purpose of this systematic review was to assess the performance of AI models in implant dentistry for implant type recognition, implant success prediction by using patient risk factors and ontology criteria, and implant design optimization combining finite element analysis (FEA) calculations and AI models.

Material and methods. An electronic systematic review was completed in 5 databases: MEDLINE/PubMed, EMBASE, World of Science, Cochrane, and Scopus. A manual search was also conducted. Peer-reviewed studies that developed AI models for implant type recognition, implant success prediction, and implant design optimization were included. The search strategy included articles published until February 21, 2021. Two investigators independently evaluated the quality of the studies by applying the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Quasi-Experimental Studies (nonrandomized experimental studies). A third investigator was consulted to resolve lack of consensus.

Results. Seventeen articles were included: 7 investigations analyzed AI models for implant type recognition, 7 studies included AI prediction models for implant success forecast, and 3 studies evaluated AI models for optimization of implant designs. The AI models developed to recognize implant type by using periapical and panoramic images obtained an overall accuracy outcome ranging from 93.8% to 98%. The models to predict osteointegration success or implant success by using different input data varied among the studies, ranging from 62.4% to 80.5%. Finally, the studies that developed AI models to optimize implant designs seem to agree on the applicability of AI models to improve the design of dental implants. This improvement includes minimizing the stress at the implant-bone interface by 36.6% compared with the finite element model; optimizing the implant design porosity, length, and diameter to improve the finite element calculations; or accurately determining the elastic modulus of the implant-bone interface.

Conclusions. AI models for implant type recognition, implant success prediction, and implant design optimization have demonstrated great potential but are still in development. Additional studies are indispensable to the further development and assessment of the clinical performance of AI models for those implant dentistry applications reviewed. (J Prosthet Dent 2023;129:293-300)

Several domains of science and engineering have been influenced by artificial intelligence (AI) and machine learning. While AI is a general term that is used for the study, development, and investigation of any computer system that exhibits "intelligent behavior,"[1,2] machine learning is a special branch of AI where the system learns specific statistical patterns in a given data set to predict the behavior of new data samples. In AI, typically, one is concerned with "intelligent agents" or agents that have both flexibility and autonomy of action.[3] Examples of AI systems such as expert systems, methods for dimensionality reduction, and probabilistic models capture some important aspect of the data set. Of those, machine learning systems offer a rich variety of algorithms and

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Clinical Implications

Artificial intelligence algorithms can provide a powerful diagnostic tool to identify dental implants by using radiographical images, predict implant survival, or assist and optimize dental implant designs.

methods particularly suited for complex prediction tasks by training the algorithms to recognize and capture statistical patterns in a given data set (that is, the training data set).[4] The primary goal of machine learning is to be able to recognize similar patterns in new data (test data) for various applications, including classification, regression, and clustering.[5]

Two distinct types of training are used in machine learning algorithms: supervised and unsupervised.[5] Tasks such as classification (determining the category of a given data point) and regression (finding a numerical relationship between a set of independent and dependent variables) are typically achieved through supervised training where the learning model is fed a set of input-output pairs of training data. Tasks such as clustering and dimensionality reduction, however, are usually accomplished through unsupervised training where the objective is simply to capture the important features in a given data set.[6] A special class of machine learning that has become popular recently is deep learning, which is an advanced methodology based on artificial neural networks.[7,8] Deep learning has found applications in many domains of engineering, health care, and data analytics in general because of its exceptional ability for generalization.[6,9] In this article, a detailed review of a wide variety of machine learning methods is provided as applied to implant dentistry.

In 2003, a systematic search found over 2000 types of dental implants.[10] The broad variability of dental implant types presents a challenging problem for dental professionals.[10,11] Different AI models have been developed for image recognition of the implant type by using periapical and panoramic radiographs.[12,13] Furthermore, AI models have also used dental radiographs to diagnose different lesions such as periodontal disease[14-17] or dental caries.[18-23] Similarly, AI applications have been reported for developing prediction models to determine osteointegration success or implant prognosis by using patient risk factors and ontology criteria, as well as optimizing dental implant designs by combining finite element analysis (FEA) calculations and AI models.[24] However, an analysis of the development performance of AI methodology and its potential influence on implant dentistry is lacking.

This systematic review aimed to analyze the performance of AI models in implant dentistry to identify implant type by using periapical and panoramic radiographs, to develop prediction models for osteointegration and forecast implant success, and to optimize implant designs.

MATERIAL AND METHODS

A population or problem, intervention, comparison, outcome (PICO) question was formulated. The population included the clinical applications in implant dentistry for implant type recognition, osteointegration success or implant success prediction by using patient risk factors and ontology criteria, and implant designs optimization by combining FEA calculations and AI models. The intervention included artificial intelligence models. The comparison was determined as nonapplicable. The outcome was the AI model performance for recognition of the implant type, forecast of the implant success by using patient risk factors and ontology criteria, and optimization of implant designs by combining FEA calculations and AI models.

Five databases were accessed without any date restriction: MEDLINE/PubMed, Embase, World of Science, Cochrane, and Scopus. Additionally, a manual search was completed (Table 1). The search strategy included articles published until February 21, 2021. All titles and abstracts were evaluated for criteria which included clinical or in vitro studies that assessed the performance of the AI models for implant type recognition, models to determine osteointegration success or implant success prediction by using patient risk factors and ontology criteria, and implant design optimization by combining FEA calculations and AI models. This systematic review conformed to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.[25]

The full text of the articles was evaluated according to the previously defined inclusion criteria. Studies not related to AI models; articles that evaluated AI applications but not for dental disciplines; investigations that examined AI models but not related with implant dentistry, such as radiology, periodontics, endodontics, pediatric dentistry, maxillofacial surgery, and orthodontics; review articles of AI applications; letters to editors; posters; AI models for tooth segmentation purposes; studies associated with dental robotics; age estimation model studies; and augmented reality applications were considered ineligible.

Two calibrated reviewers (M.R.-L., M.G.-P.) gathered the data from the included articles into tables. Disagreements were resolved by consensus with a third examiner (V.R.K.). The quality of the investigations was

Table 1. Boolean search strategy formulated on 5 databases investigated

Database	MeSH Terms and Search Terms
MEDLINE/PubMed	("dental implants" [MeSH] OR "dental prostheses, implant-supported" [MeSH] or "Dental implant, single tooth" [MeSH] OR "Alveolar bone loss" [MeSH] or "alveolar bone" or "dental implant" OR "dental prostheses implant-supported") AND ("Artificial intelligence" [MeSH] OR "Computational Intelligence"OR "Machine Intelligence" OR "Computer Reasoning" OR "AI-based" OR "Computer Vision Systems" OR "Knowledge Acquisition" OR "Knowledge Representation" OR "Machine learning" [MeSH] OR "Deep learning" [MeSH] OR "Supervised machine learning" [MeSH] OR "Unsupervised Machine Learning" [MeSH] OR "Expert systems" [MeSH] OR "Fuzzy Logic" [MeSH] OR "Natural Language Processing" [MeSH] OR "Neural Networks, Computer" [MeSH])
Embase, World of Science, Cochrane, and Scopus	("dental implants" OR "dental prostheses implant-supported" OR "Dental implant, single tooth" OR "Alveolar bone loss" OR "alveolar bone" OR "dental implant" OR "dental prostheses implant-supported") AND ("Artificial intelligence" OR "Computational Intelligence" OR "Machine Intelligence" OR "Computer Reasoning" OR "AI-based" OR "Computer Vision Systems" OR "Knowledge Acquisition" OR "Knowledge Representation" OR "Machine learning" OR "Deep learning" OR "Supervised machine learning" OR "Unsupervised Machine Learning" OR "Expert systems" OR "Fuzzy Logic" OR "Natural Language Processing" OR "Neural Networks, Computer") NOT (MEDLINE)

Table 2. Joanna Briggs Institute Critical Appraisal Checklist for Quasi-Experimental Studies (nonrandomized experimental studies)

Question	Answer
1 Is it clear in the study what is the 'cause' and what is the 'effect' (that is, there is no confusion about which variable comes first)?	Yes, No, Unclear, or Not applicable
2 Were the participants included in any similar comparisons?	
3 Were the participants included in any comparisons receiving similar treatment/care other than the exposure or intervention of interest?	
4 Was there a control group?	
5 Were there multiple measurements of the outcome both before and after the intervention/exposure?	
6 Was follow-up complete and, if not, were differences between groups in terms of their follow-up adequately described and analyzed?	
7 Were the outcomes of participants included in any comparisons measured in the same way?	
8 Were outcomes measured in a reliable way?	
9 Was appropriate statistical analysis used?	

assessed by applying the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Quasi-Experimental Studies (nonrandomized experimental studies) (Table 2).[26] Similarly, the third examiner (V.R.K.) was consulted to resolve lack of consensus.

RESULTS

The search strategies yielded 207 studies. A total of 21 duplicates were found. The 186 remaining articles were evaluated by the titles and abstracts. Twenty-six articles were identified for full-text revision. Nine articles were excluded after full-text review, 2 excluded articles exposed a conceptual methodology, 1 applied AI models for implant placement accuracy improvement evaluation by using robotics, 2 articles did not describe the AI model, 1 study applied AI models to improve the data search on systematic reviews, 2 studies used an AI model to predict future developments by clustering patents and clinical implant studies, and 1 investigation was not related to AI (Fig. 1).

Seventeen articles published between 2005 and 2020 were included in the present investigation (Fig. 2). The AI models used among the different studies are presented in Table 3. The selected articles were distributed into 3 groups depending on the application of the AI model: implant type recognition (Supplementary Table 1, available online),[13,27-32] models to determine osteointegration success or implant success prediction by using patient risk factors and ontology criteria (Supplementary Table 2, available online),[33-39] and implant design optimization by combining FEA calculations and AI models (Supplementary Table 2, available online).[40-42]

The overall accuracy outcome of the AI models developed in the different reviewed studies ranged from 93.8% to 98%.[13,27-32] The AI models to predict osteointegration or implant success by using different input data varied among the studies ranging from 62.4% to 80.5%.[33-39] Finally, the studies that developed AI models to optimize implant designs seem to agree on the applicability of AI models to improve implant designs, minimizing the stress at the implant-bone interface by 36.6% compared with the FEA model,[40] optimizing the implant design porosity, length, and diameter, improving the FEA calculations,[41] or accurately determining the elastic modulus of the implant-bone interface.[42]

With respect to the selection of articles by reviewing their titles and abstracts, there was significant agreement between the 2 investigators for the articles that were selected (Cohen Kappa=0.97, $P<.001$) and the articles that were not selected (Cohen Kappa value=0.97, $P<.001$). With respect to the selection of articles by reviewing their full text, there was a significant agreement between the 2 investigators for the articles that were selected (Cohen Kappa value=1, $P<.001$) and the articles that were not selected (Cohen Kappa value=1, $P<.001$).

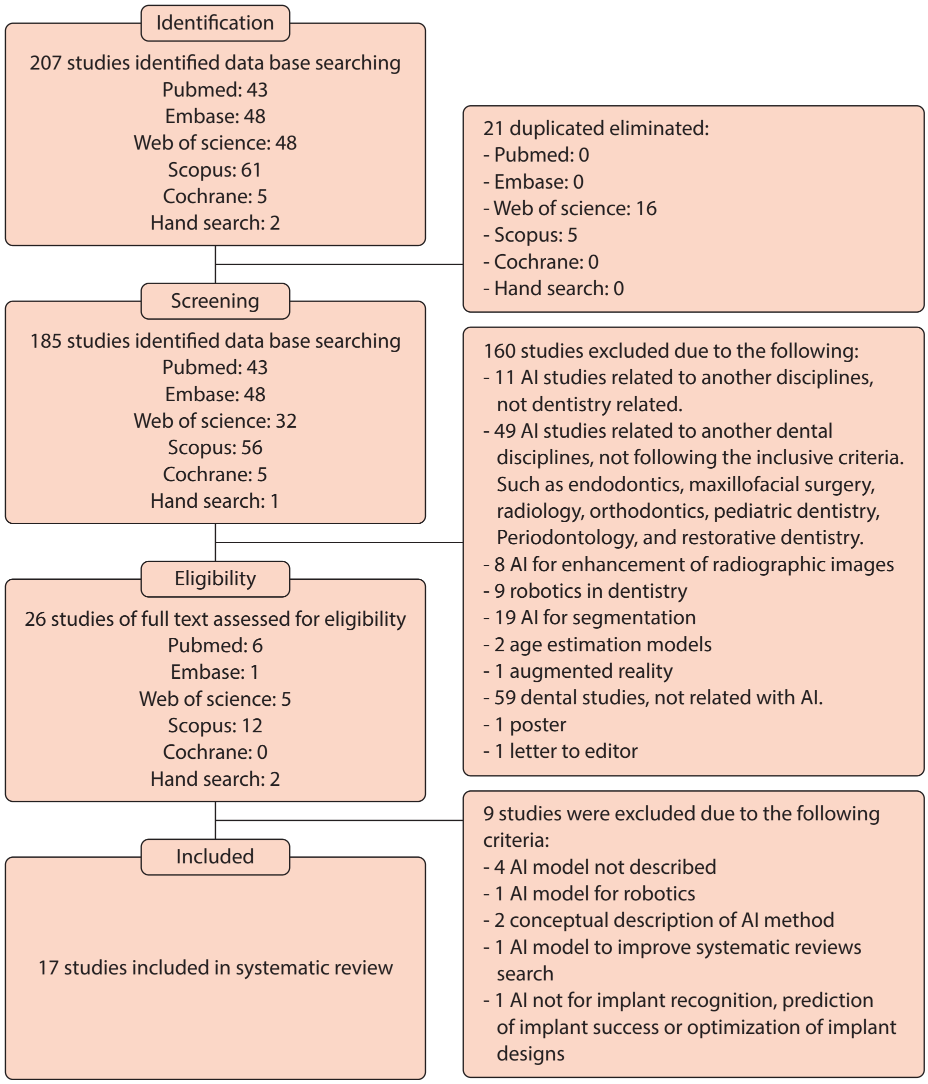

Figure 1. PRISMA flow diagram with information through phases of study selection.

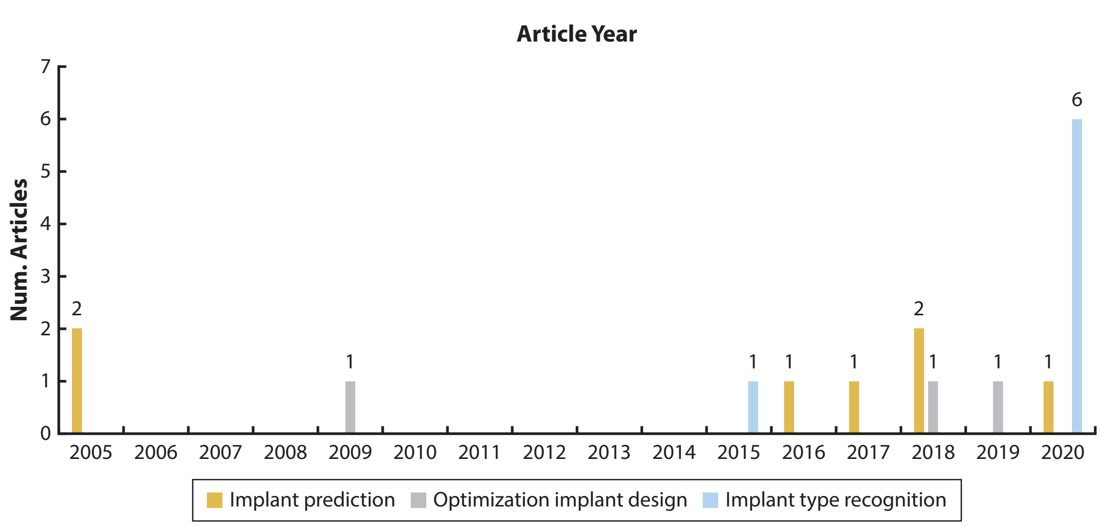

Figure 2. Number of included articles by year and purpose of artificial intelligence model.

Table 3. Artificial intelligence models used in articles included in systematic review

Classical Machine Learning	Artificial Neural Networks
Regression analysis: Estimates the relationship among variables. • Support Vector Machine (SVM) (classification)[33-39] • Support Vector Regression (SVR)[40] • k-Nearest Neighbors (k-NN) (supervised learning, classification)[13,36,37,39] • k-Means clustering (clustering)[36]	Artificial neural networks or neural networks: Linked units named artificial neurons which receives and processes a signal. The connections are called edges. Neurons are usually collected into layers. • Naïve Bayes[37] • Deep Convolutional Neural Networks (CNN)[27-32] • Residual Neural Network[30,32] • Artificial Neural Networks (ANN)[33,37-39,41,42]
Decision tree learning: Prediction model using classification tree[34,35] • Random forest[33]	
Logistic regression (LR): Used as a classification model[33,35]	
Multidimensional unfolding analysis (MDU)[36]	
Ensemble-based models: Combination of different models to improve accuracy (such as, Bagging, Adaboost)[35,37]	

The JBI Critical Appraisal Checklist for Quasi-Experimental results showed a 100% low risk of bias in all included articles for question 8. For question 1, all the studies obtained a low risk of bias except for that of Morais et al[13] that obtained a high risk of bias. For question 4, all the investigations attained a low risk of bias except for those of Hadj Saïd et al,[27] Papantonopoulos et al,[36] Zaw et al,[42] Sukegawa et al,[29] Ha et al,[34] Morais et al,[13] Takahashi et al,[32] and Kim et al[30] that showed a high risk of bias. For question 9, all the studies displayed a low risk of bias except for that of Zaw et al[42] that did not have statistical analysis. As no specific in vitro study quality assessment tool has been developed, questions 2 and 6 of the JBI were not applicable in this systematic review. Questions 3, 5, and 7 were not applicable for any of the included studies (Fig. 3).

DISCUSSION

The number of publications that use AI models for implant dentistry applications has risen notably since 2018. The year ranged from 2005 to 2020, with very few publications before 2005.

A total of 7 included studies developed AI models for implant type recognition. Except 1 study that used regression analysis k-nearest neighbors (k-NN), all the studies selected developed a convolutional neural network (CNN) — a deep neural network algorithm for image recognition and classification by using as an input radiographical data such as periapical[27,28,30,31] and panoramic images -,[27-29,31,32] or the type of radiographical data was not provided.[13] The efficacy comparisons among the different AI models used are difficult because of the data input or methods used on the studies reviewed. While each study attempted to standardize the collection of the radiographical data set, differences among the studies were identified, including projection geometry, exposure factors, film contrast, and film speed. Furthermore, variations on the radiographic information differed among the reviewed studies where the implant by itself (with a cover screw or a healing abutment) or with the prosthetic part was visible on the radiographical images; therefore, comparisons among the different studies are difficult.

All the reviewed studies that developed AI models for implant type recognition used 2-dimensional (2D) radiography as the input data set. A diversity of deep CNN architectures has been dedicated and trained by using 3-dimensional (3D) computed tomographic images.[43,44] Two-dimensional images including periapical and panoramic radiographs are more distorted than 3D scans. Even though clinicians normally obtain periapical radiographs for the radiographic evaluation of dental implants, the inclusion of cone beam computed tomography (CBCT) images might aid in the AI development for the recognition of dental implant types. All the included studies used CBCT images to develop the AI model.

Considering the broad implant types available in the market,[10] limited implant types were analyzed in different reviewed studies. Furthermore, implant designs can be different from each other, facilitating AI recognition among the different implant types analyzed in a study, while other implant designs are similar, which may require a data base large enough to train the AI model to differentiate them. However, the overall accuracy outcome of the AI models developed in the different reviewed studies ranged from 93.8% to 98%.[13,27-32]

Lee and Jeong[28] used a data set of 10 770 radiographic images from 3 different implant types to train a deep CNN model. The authors compared the implant recognition capabilities of the examiners (board-certified periodontists and the AI model) and of the radiographical image used: periapical, panoramic, or both images. Implant recognition accuracy varied among the 3 types of implants tested, but higher specificity and sensitivity were found when both periapical and panoramic images were used for both the AI model and the periodontists.

While in other medicine specialties different registering strategies have developed orthopedic records,[45] one of the current limitations in implant dentistry is the absence of available data records which can facilitate AI

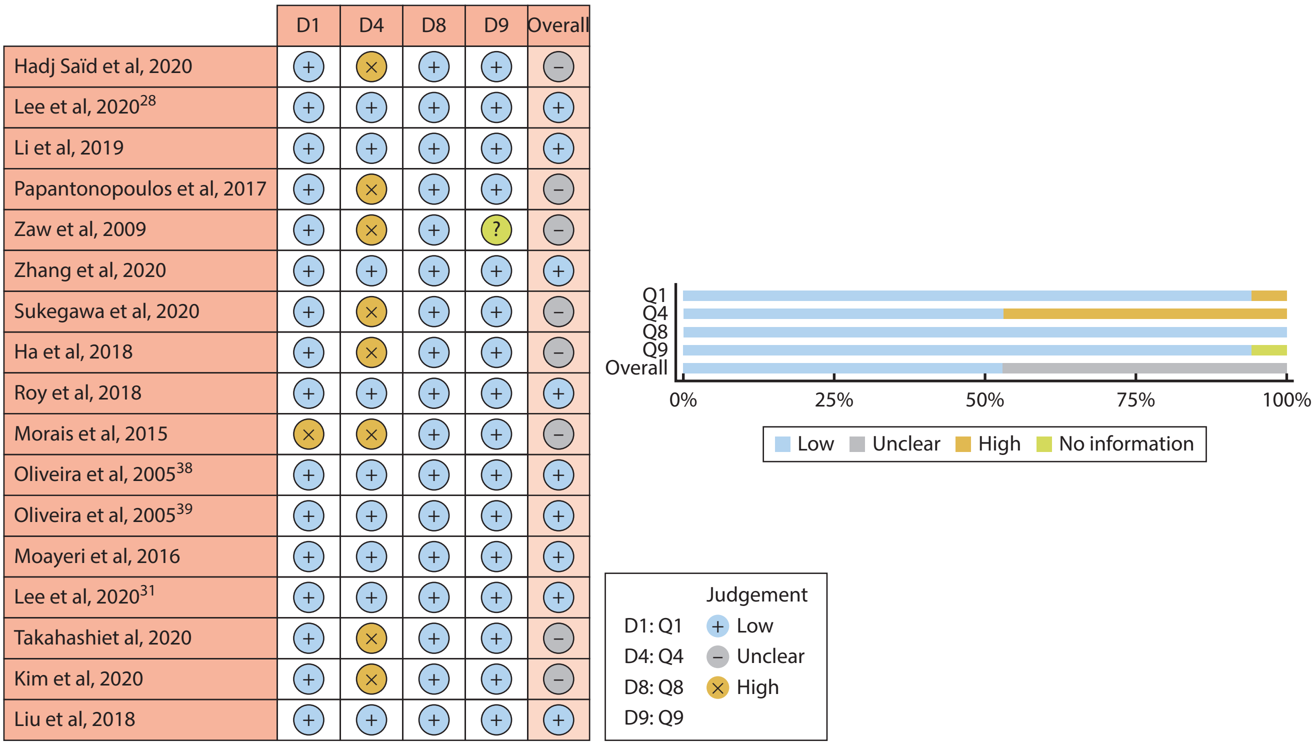

Figure 3. Joanna Briggs Institute JBI Critical Appraisal Checklist for Quasi-Experimental evaluation.

model development and training on implant recognition. However, the clinical applicability of such an AI application would help clinicians trying to restore an unknown implant. Furthermore, clinicians that have less clinical experience in implant dentistry may obtain assistance by using an implant recognition software program.

A total of 7 included studies aimed to develop AI models to predict implant success by using a broader variety of AI models compared with the implant recognition AI application. The main AI models used were regression analysis (support vector machine classification), decision tree learning, logistic regression, and classifier neural network.[33-39] However, because of a high variation in the methodologies among the different studies, comparisons among the obtained results are difficult.

Prediction models are based on clustering data and investigating the structural properties of the data network generated by intricate relations of demographic, radiographical, and clinical variables. Therefore, the prediction AI algorithm is assembled based on the input data provided. Most of the included studies used demographic data, physical and intraoral conditions, lifestyle, anatomic condition of the area receiving the implant, implant placement with or without bone grafting procedures, bone levels around the implant measured by using periapical radiographs, or characteristics of the prosthesis as an input. Furthermore, most of the reviewed studies did not include the implant type used, a definition of implant success, implant prosthesis design, and genetic, immunological, or microbiological variables, which might have impacted the results. Because of methodological discrepancies, comparisons among the different studies were not feasible.

Papantonopoulos at al[36] aimed to cluster demographic, clinical, and radiographic data from 72 patients with 237 implants and recognize potential implant "phenotypes" and forecasters of bone levels around implants. The AI model produced an implant map establishing the existence of 2 distinct implant clusters, which the authors identified as 2 possible types of implant "phenotypes," namely implant phenotype with susceptibility or resistance to peri-implantitis. The interpretation of the data is interesting, as the AI model was developed by using the data obtained from 1 private practice which might not represent the general population. The limited data and measurements collected by 1 periodontist, the restricted patient follow-up period of 2 years, or implants placed with bone grafting procedures were excluded. The difficulty of obtaining data to develop and train AI models is a challenge for researchers, limiting the faster development of AI models in implant dentistry.

Three included studies applied AI models for implant design optimization by using finite element analysis (FEA) methods.[40-42] Li et al[40] replaced the FEA model with an AI algorithm to compute the stress at the implant-bone interface by considering 3 implant design variables, namely the implant length, thread length, and thread pitch. The AI model sought to optimize the implant design variables to minimize the stress at the implant-bone interface. The results of this study showed a reduction of 36.6% of the stress at the implant-bone interface compared with the FEA model. Roy et al[41] aimed to optimize the implant design porosity, length, and diameter by using an artificial neural network (ANN) combined with genetic algorithms by substituting the FEA calculations. Similarly, Zaw et al[42] developed a reduced-basis method of creating the reactions of the dental implant-bone system to develop a neural network architecture. The proposed AI algorithm was capable of accurately computing the elastic modulus of the implant-bone interface. All the studies agreed on the applicability of AI models to optimize implant designs; however, further investigations are needed to improve the AI calculations on implant design and evaluating the outcomes in in vitro, animal, and clinical studies.

Future directions in implant dentistry could combine CBCT scans with radiographic image data to aid in data analysis and increase the accuracy of implant type recognition. The implementation of a special class of deep learning methods such as 1-shot learning and less-than-1-shot learning that require fewer data points than neural network models might facilitate the implementation and improvement of AI models for implant dentistry applications. Furthermore, the standardization and benchmarking of data sets might increase the accuracy of AI models in identifying implant type or predicting implant success. The availability of open data sets will promote the growth of AI models.

CONCLUSIONS

Based on the findings of this systematic review, the subsequent conclusions were drawn:

1. AI models have the potential to recognize implant type, predict implant success by using patient risk factors and ontology criteria, and optimize implant designs, but they are still being developed. With its application in implant dentistry rapidly expanding, the effectiveness and reliability of AI models should be evaluated before recommending them for clinical practice.
2. Based on the reviewed studies, the AI models developed to recognize implant type by using radiographical images were the more developed application of AI in implant dentistry, obtaining an overall accuracy ranging from 93.8% to 98%.
3. The AI models to predict osteointegration or implant success varied from 62.4% to 80.5% among the studies.
4. The studies that developed AI models to optimize implant designs seem to agree on the applicability of AI models to improve implant designs, minimizing the stress at the implant-bone interface by 36.6% compared with the FEA model, optimizing the implant design porosity, length, and diameter, improving the FEA calculations, or accurately determining the elastic modulus of the implant-bone interface.

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