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SYSTEMATIC REVIEW

Artificial intelligence applications in restorative dentistry: A systematic review

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ABSTRACT

Statement of problem. Artificial intelligence (AI) applications are increasing in restorative procedures. However, the current development and performance of AI in restorative dentistry applications has not yet been systematically documented and analyzed.

Purpose. The purpose of this systematic review was to identify and evaluate the ability of AI models in restorative dentistry to diagnose dental caries and vertical tooth fracture, detect tooth preparation margins, and predict restoration failure.

Material and methods. An electronic systematic review was performed in 5 databases: MEDLINE/PubMed, EMBASE, World of Science, Cochrane, and Scopus. A manual search was also conducted. Studies with AI models were selected based on 4 criteria: diagnosis of dental caries, diagnosis of vertical tooth fracture, detection of the tooth preparation finishing line, and prediction of restoration failure. Two investigators independently evaluated the quality assessment 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. A total of 34 articles were included in the review: 29 studies included AI techniques for the diagnosis of dental caries or the elaboration of caries and postsensitivity prediction models, 2 for the diagnosis of vertical tooth fracture, 1 for the tooth preparation finishing line location, and 2 for the prediction of the restoration failure. Among the studies reviewed, the AI models tested obtained a caries diagnosis accuracy ranging from 76% to 88.3%, sensitivity ranging from 73% to 90%, and specificity ranging from 61.5% to 93%. The caries prediction accuracy among the studies ranged from 83.6% to 97.1%. The studies reported an accuracy for the vertical tooth fracture diagnosis ranging from 88.3% to 95.7%. The article using AI models to locate the finishing line reported an accuracy ranging from 90.6% to 97.4%.

Conclusions. AI models have the potential to provide a powerful tool for assisting in the diagnosis of caries and vertical tooth fracture, detecting the tooth preparation margin, and predicting restoration failure. However, the dental applications of AI models are still in development. Further studies are required to assess the clinical performance of AI models in restorative dentistry. (J Prosthet Dent 2022;128:867-75)

The term artificial intelligence (AI) has been defined as the capability of an engineered system to acquire, process, and apply knowledge and skills acquired through experience or education that are generally associated with human intelligence.[1,2] AI is a broad field of research that studies "intelligent agents" or agents that are capable of flexible autonomous action.[3] AI systems come in a variety of forms ranging from expert systems to systems that learn complex computational models from data to perform predictions on new information. The second category of systems includes machine learning systems that are rich in terms of their tools, techniques, and algorithms.[4] Machine learning refers to a class of AI algorithms and models that are "trained" to capture statistical

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Clinical Implications

Artificial intelligence models have the potential to provide a powerful diagnostic tool to diagnose dental caries and vertical tooth fracture, improve the automatic detection of the tooth finishing line, and predict the dental restoration failure.

patterns in a given data set (called the training data) with the goal of recognizing similar patterns in new data (test data).[5] Such pattern recognition can be useful in a variety of tasks such as classification (predicting the category of a given data point from a set of predefined categories), regression (predicting values of a function for a given input), and clustering (grouping the elements of a dataset based on similarity or other measures).[5]

Machine learning algorithms can be trained in 2 different ways: supervised or unsupervised.[5] Supervised learning refers to a methodology wherein each data point in the training data consists of input-output pairs where the model is exposed to several inputs for which the output is known. The goal for the training is to capture the relationship between the input and output so that the model can then predict the output for a test data input. Object classification and regression are mostly achieved through unsupervised learning. In case of unsupervised learning, such a data set without explicit instructions on what to do with it is provided. The goal of unsupervised learning is mainly to identify patterns by extracting the most relevant features from a data set.[6] As a result, unsupervised learning is used commonly for tasks such as data clustering and dimensionality reduction. Recently, a special class of machine learning methods, deep neural networks, have become popular in several fields.[7,8] Deep neural networks are extensions of artificial neural networks modeled after the brain, wherein a connected set of layers of nodes are trained on an input data set to perform several machine learning tasks such as classification, regression, and clustering.[6,9]

Different forms of AI have started to impact dentistry, including image enhancement for radiology,[10-12] the diagnosis of cysts and tumors,[13-18] the diagnosis of periapical lesions and root anatomy identification for endodontics,[19-21] the diagnosis of periodontitis,[10,22] and for automated location of cephalometric landmarks in orthodontics.[23-26]

In restorative dentistry, different AI applications have been evaluated.[10,27] However, to realize the potential of AI methodologies in restorative dentistry, a systematic categorization and characterization of the development, performance, and limitations of AI is needed. This systematic review aimed to identify and evaluate the performance of the AI in restorative dentistry. The review focused on the diagnosis of dental caries and vertical tooth fractures, detection of the tooth preparation margin, and prediction of restoration failure.

MATERIAL AND METHODS

The problem or population, intervention, comparison, outcome (PICO) question was defined as follows: the population comprised the clinical applications in restorative dentistry for the diagnosis of dental caries and vertical tooth fracture, detection of the tooth preparation finishing line, and prediction of restoration failure; the intervention included artificial intelligence learning; the comparison was determined as nonapplicable; and the outcome was the diagnostic performance of the AI model for the diagnosis of dental caries and tooth fracture, the accuracy of tooth preparation finishing line location, and the prediction of restoration failure. Five different databases were selected without any date restriction: MEDLINE/Pubmed, EMBASE, World of Science, Cochrane, and Scopus. A manual search was also conducted (Table 1). All titles and abstracts were first assessed for the following inclusive criteria which included clinical or in vitro studies that evaluated the performance of the AI models in the diagnosis of dental caries and tooth fractures, detection of the tooth preparation margin, and prediction of restoration failure. This systematic review conformed to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.[28]

After evaluating the full text of the articles according to the previously defined inclusive criteria, AI studies related to another disciplines or dental disciplines but not related with restorative dentistry were considered ineligible; for example, endodontics, periodontics, maxillofacial surgery, pediatric dentistry, and orthodontics, or tooth segmentation studies, review articles of AI models, AI model not described, letter to editors, studies related to robotics in dentistry, radiographic and cone bean computed tomography (CBCT) enhancement investigations, and age estimation model studies based on development of permanent teeth. Two calibrated reviewers (M.R.L., M.G.P.) collected the data from the selected articles into structured tables. Discrepancies were resolved by consensus, and a third examiner (V.K.) was consulted.

The same 2 review authors independently evaluated the quality assessment of the studies by applying the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Quasi-Experimental Studies (nonrandomized experimental studies) (Table 2).[29] The third examiner (V.K.) was consulted to resolve lack of consensus.

RESULTS

The Cohen kappa values between examiners were 0.974 ($P<.001$), indicating substantial agreement between the

Table 1. Boolean search strategy used on 5 databases explored

Database	MeSH Terms and Search Terms
MEDLINE/PubMed	("Tooth preparation"[MeSH] OR "Dental prosthesis"[MeSH] OR "Tooth crown"[MeSH] OR "crowns"[MeSH] OR "bridge" or "fixed dental prosthesis" OR "intraoral scanner" OR "intraoral scan" OR "intraoral digital scan" OR "digital impression" OR "Dental caries"[MeSH] OR "Decay" OR "Carious dentin" OR "Tooth"[MeSH]) 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	("Tooth preparation" OR "Dental prosthesis" OR "Tooth crown" OR "crowns" OR "bridge" or "fixed dental prosthesis" OR "intraoral scanner" OR "intraoral scan" OR "intraoral digital scan" OR "digital impression" OR "Dental caries" OR "Decay" OR "Carious dentin") 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]/lim AND [embase]/lim.

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" (ie, 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 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?	

examiners. The AI models found are presented in Table 3. Figure 1 represents the number of publications per year classified into 4 groups based on the application of the AI model. The search strategies yielded 1596 studies. After evaluating the titles and abstracts, 38 articles were identified, 4 of which were excluded after full-text revision (Fig. 2). The selected articles were classified into 4 groups based on the application of the AI model: the diagnosis of dental caries and elaboration of caries and postsensitivity prediction models,[30-56,59,60] diagnosis of vertical tooth fracture,[20,61] detection of the tooth preparation finishing line,[62] and prediction of restoration failures.[57,58]

For the diagnosis of dental caries, a total of 29 articles were included. Eighteen studies used periapical and/or bitewings radiographs,[30-39,45,47-52,54,59] 5 studies used intraoral photographs,[42-44,53,55] 1 study analyzed the near-infrared transillumination techniques,[56] and 1 study evaluated the fiber optic displacement sensor as the input source.[46] Another AI application described was the elaboration of caries[40,41,60] and postsensitivity prediction models after the performance of a direct restoration (Supplementary Tables 1-3, available online).[45] Two articles that included AI models for the diagnosis of vertical tooth fracture using periapical radiographs[61] and/or CBCT images[20] were included in the review (Supplementary Table 4, available online). One included article[62] used AI techniques to detect the finishing line of tooth preparation (Supplementary Table 5, available online), and 2 included articles[57,58] used AI techniques to predict restoration failure (Supplementary Table 6, available online).

The JBI Critical Appraisal Checklist for Quasi-Experimental results showed a 100% low risk of bias in all included articles for questions 1, 8, and 9. For question 4, 60% of low risk and 40% of high risk of bias was computed because of the high risk of bias found in Aliaga et al,[58] Casalegno et al,[56] Gakenheimer,[48] Moutselos et al,[53] Moustselos et al,[55] Lee et al,[54] Pitts,[30,32] Pitts and Renson,[31,33] Rahman et al,[46] Vladimirov et al,[45] and Yamaguchi et al.[57] Since 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 (Fig. 3).

DISCUSSION

The number of publications that use AI methods in restorative dentistry has increased considerably in the last 2 years but was sparse in previous years. Sophisticated AI models were slow to develop after 1984, but this has been followed by a sudden rise in the adoption of machine learning across various scientific domains since 2015. AI learning techniques were slow to be adopted in

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

Expert Systems	Classical Machine Learning Models	Artificial Neural Networks
Computer programs that take decisions based on a set of expert heuristics[30-39]	Regression analysis: Estimates the relationship among variables.[40,41]	Artificial neural networks (ANN) or neural networks (NN): is based on a collection of connected units or nodes called artificial neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The connections are called edges. Typically, neurons are aggregated into layers.
	• Support vector machine (SVM)[41-44]	• Classifier NN[40,42]
	• k-nearest neighbors (k-NN)[41]	• Perceptron NN[45,46]
	Decision tree learning: Prediction model using classification tree.	• Multi Layered Perceptron (MLP)[47,58]
	• Random tree[43,44]	• Back-Propagation NN[48-52]
	• Random forest[41-44,53]	• Convolutional Neural Networks (CNN)[54-58]
	Fuzzy logic learning: Generates levels of possibilities of input to achieve definite output.[39,45,46,59]	• Probabilistic neural network (PNN)[60-62]
	Case-based reasoning: Manages cases (past experiences) to solve new problems.[58]	• Deep neural network (DNN)

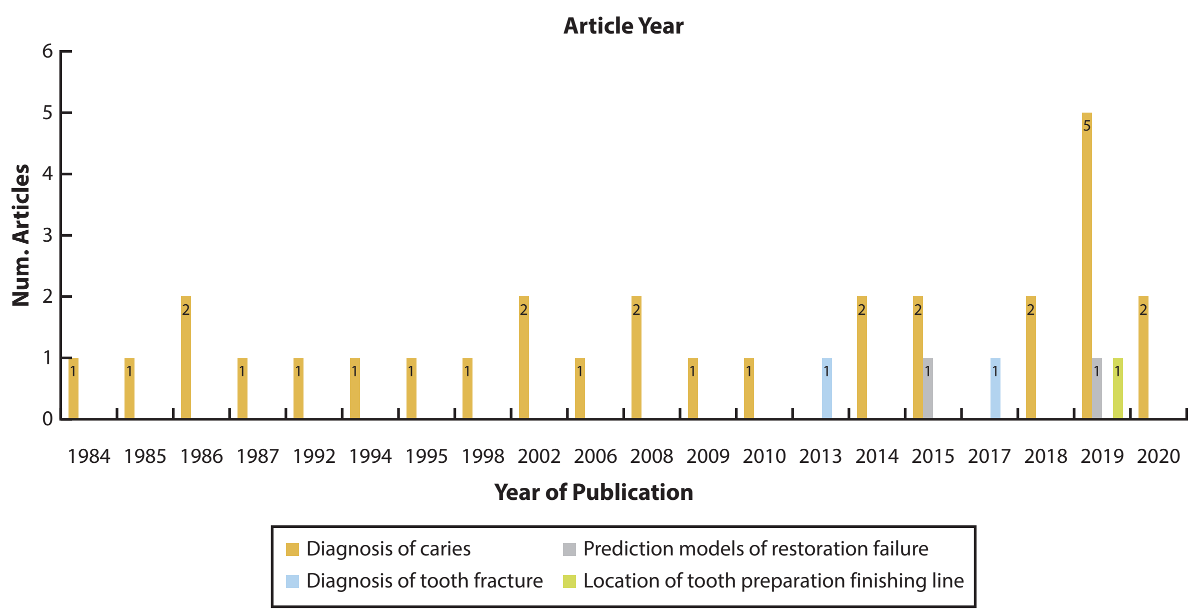

Figure 1. Number of included articles by year and purpose of artificial intelligence model.

dentistry, possible because of sparse access to well-labeled patient data.

Eighteen of the 29 articles included in the present systematic review evaluated different AI models for the diagnosis of dental caries by using periapical and/or bitewing radiographs.[30-39,45,47-52,54,59] The AI models included expert systems,[30-39] regression analysis,[40] fuzzy logic learning,[39,45,59] perceptron neural networks,[45] multilayer perceptron,[47] back-propagation neural networks,[48-51] and convolutional neural networks.[54] Twelve of those studies were based on radiographic images of extracted human teeth,[31-38,47,49-51,59] and 6 on clinical radiographs.[31-33,39,48,52,54] One study did not specify the origin of the radiographs.[30] 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.

Five studies compared the radiographic assessment of the AI model for the diagnosis of dental caries with histological analysis of the extracted specimens.[33,47,49,50,59] Eight studies compared the outcome of the AI model with the radiographic evaluation completed by clinicians[34-38,48,49,51] or other AI models.[39] The majority of the studies reported improvement in the diagnosis of dental caries when using the software program,[34-36,38,47,48,51] 1 study reported no significant differences,[37] and 2 studies concluded that the clinicians were able to provide more accurate caries diagnoses than the AI software program.[49,50]

The distinction between enamel and dentin caries is critical when diagnosing dental caries; however, not all

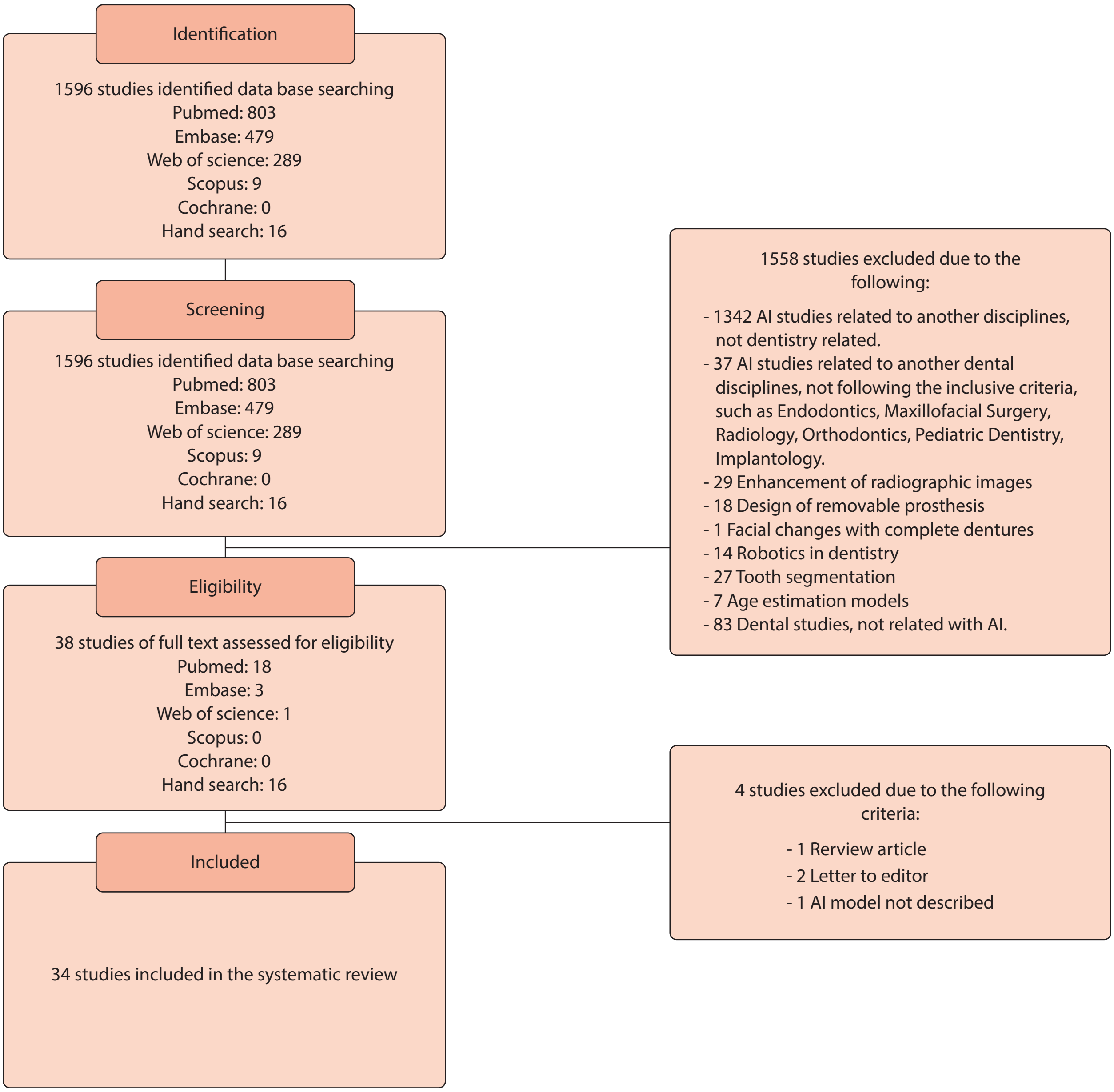

Figure 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram with information through phases of study selection.

the studies considered the extension of caries into dentin,[35,49-51,59] only classifying the lesions as present or absent.[30-34,36-39,47-49,52,54] Valizadeh et al[59] analyzed an AI model to diagnose proximal caries from periapical radiographs and compared the AI model outcome with a histological examination of the specimens. The software program was able to diagnose 97% of the dentin carious lesions but only 60% of the enamel carious lesions. Similarly, Devito et al[47] evaluated an AI model to diagnose proximal caries from bitewing radiographs and performed the histologic evaluation of the extracted human teeth used in the project. The results showed better caries proximal diagnosis for the AI software program than for the most accurate examiner.

The evaluation of radiographic images to assess the presence or absence of carious lesions during the training phase of the AI models was accomplished differently among the studies. The training data set is the fundamental information from which the AI model is developed; therefore, the ground truth might not necessarily represent the real truth. Variations were found in the number of images contained in the training, validation, and test data sets among the reviewed studies.

Among the studies reviewed, the AI models obtained a caries diagnosis accuracy ranging from 76% to 88.3%, sensitivity ranging from 73% to 90%, and specificity ranging from 61.5% to 93%. However, comparisons

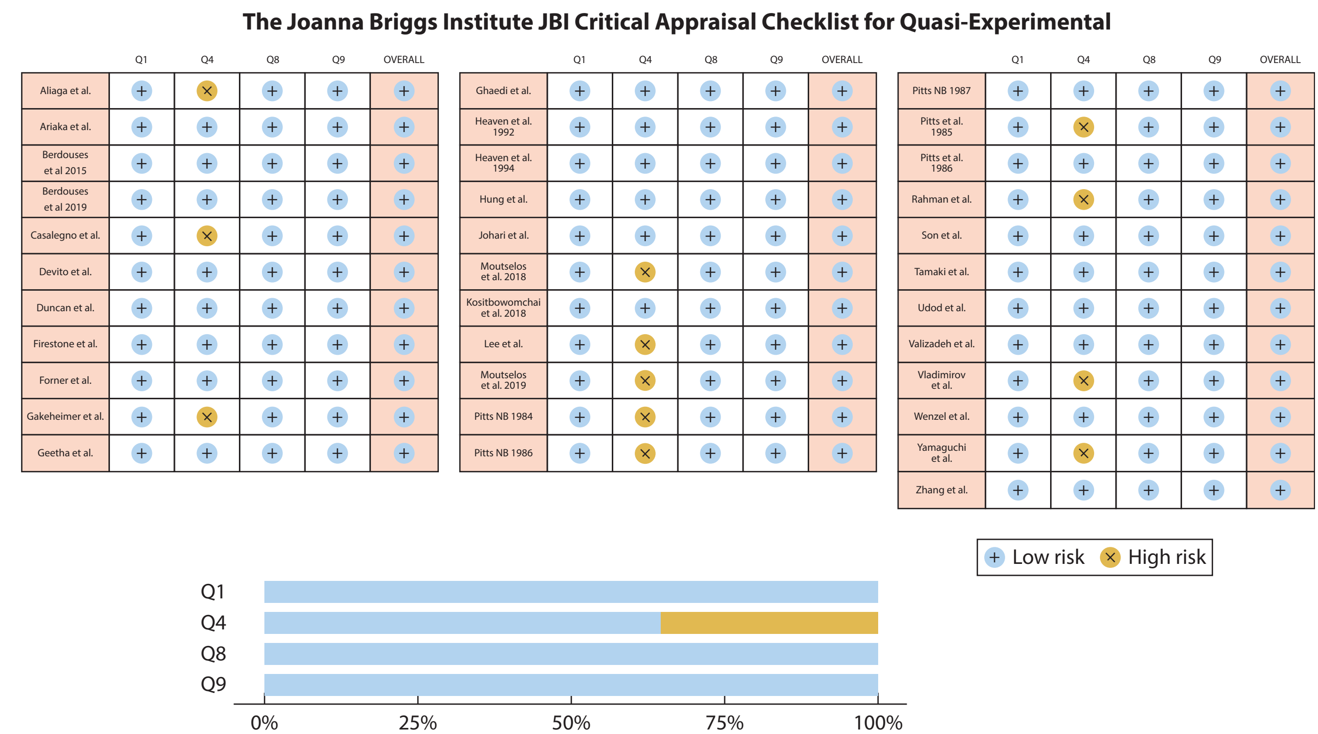

Figure 3. Joanna Briggs Institute Critical Appraisal Checklist for Quasi-Experimental evaluation.

among the studies were difficult because of disparities in the methods used.

Different AI models using intraoral photographs, including methods such as regression analysis[42,43] and decision tree learning,[44,53] and artificial neural networks such as convolutional neural networks were used to diagnose dental caries.[55] Five studies developed AI models to diagnose dental caries by using clinical occlusal photographs,[42-44,55] 4 of which used extracted human teeth,[42-44,53] and 2 studies evaluated clinical intraoral photographs.[43,55] Different standardization settings for the analysis of the photographs were found among the different studies, such as resolution, magnification, illumination, or white balance, which might also have influenced the results.

When occlusal photographs were used as an input source, all the reviewed studies used the international caries detection and assessment system (ICAD) to assess and classify the extension of dental caries.[42-44,53,55] In the majority of the studies reviewed, the image assessments were performed by ICAD experts or experienced clinicians,[42,43,53,55] and only 1 study compared the visual assessment with histologic results.[44] These evaluations were used as a ground truth during the AI training phase, which might have provided an incorrect training dataset.

The AI models using intraoral photographs showed an accuracy for the dental caries diagnosis ranging from 80% to 86.3%, a specificity ranging from 95.6% to 98.3%, and a sensitivity ranging from 80% to 100%. However, comparisons among the studies were difficult because of disparities in the methods used.

Only 1 study developed a convolutional neural network (CNN) AI model to diagnosis dental caries by using near-infrared transillumination imaging.[56] An accuracy of 72% was reported, obtaining better results when diagnosing dentin than enamel caries. Only 1 study included aimed to determine the dimensions of cavitated tooth surfaces by using a fiber optic displacement sensor (FODS).[46] The fuzzy logic and single-layer perceptron (SLP) neural network AI model developed in this study reported a 100% success rate for the diagnosis of tooth cavities of up to 0.6 mm.[46]

Three studies intended to generate caries prediction models to facilitate the likelihood calculation of an individual developing dental caries based on clinical findings,[40,60] or demographic and lifestyle factors.[41] The AI models used were regression analysis,[40] probabilistic neural networks,[41] and random forest of the decision tree leaning.[60] The methodology used varied among the studies as to how the data were collected and analyzed and the AI model developed. Therefore, a comparison of the studies was difficult. The caries prediction accuracy among the studies ranged from 83.6% to 97.1%.[40,41,60]

One study applied an AI model to find relationships between contributing factors to postoperative sensitivity.[45] The data were obtained by using a survey regarding the dentist's experience in diagnosing postoperative sensitivity. The authors defined some relationships between postoperative sensitivity and associated factors. However, the results presented showed the clinical experience of the surveyed dentists.

Two in vitro studies developed AI models for the diagnosis of vertical tooth fracture.[20,61] Kositbowornchai et al[61] included periapical radiographs of 200 extracted but not endodontically treated premolars, reporting an accuracy ranging from 88.3% to 95.7%, a sensitivity ranging from 97.2% to 98%, and a specificity ranging from 60% to 90.5%. Similarly, Johari et al[20] obtained 240 extracted premolars, with and without endodontic treatment. The AI model was used to diagnose vertical fracture from periapical radiographs and CBCT images. The results showed higher accuracy, sensitivity, and specificity from CBCT images than from radiographs. The methodology of both studies did not require expert assessment of the tooth fracture diagnosis, which might minimize error in the ground truth.

Only 1 study developed a CNN AI model to locate the tooth preparation finishing line for crowns.[62] The study obtained 380 tooth preparation virtual dies of premolar and molars for crowns from an unidentified source. However, the analysis of different variables, such as the type and depth of the finishing line and conicity, for the tooth preparation or the method used to prepare the virtual die were not described, which might have influenced the outcomes of the AI model. The average accuracy of the finishing line location with the CNN model ranged from 90.6% to 97.4%.

Two included studies attempted to develop an AI model to predict the failure of crowns by using images captured from the dies of virtual tooth preparations and to identify the preferred restorative material and predict its longevity.[57,58] Yamaguchi et al[57] attempted to predict the debonding of composite resin crowns by developing a CNN AI model. The authors collected records from 24 composite resin crowns with their corresponding virtual tooth preparation die files, where 50% of the crowns had debonding problems. A total of 640 two-dimensional images of the virtual tooth preparation 3-dimensional dies were used to correlate the debonding records. The model was able to predict the debonding failure by using the images of the tooth preparation with a 98.5% prediction accuracy. Only the variable of tooth preparation shape was considered to develop the AI model and predict the debonding failure of the restoration. However, other factors such as the clinical situation of the tooth receiving the restoration, cement selected, or cementation protocol used were not considered and might have influenced the debonding and failure of the restorations.

Aliaga et al[58] used a case-based learning model to identify the preferred restorative material (composite resin or amalgam) for direct restoration and to predict the longevity the restorations. Information from 2023 patients was collected, including characteristics of the tooth receiving the direct dental restoration and characteristics of the patient. The authors concluded that the model could determine the type of restoration that was best suited to the patient by predicting the longevity of each procedure. The criteria for defining the selection of the restorative material of the data collected were based on the experience of the faculty members of a dental school and clinicians in private practice who were participating in the study.

Future directions in restorative dentistry could combine intraoral scans with image data to complement the data analysis and increase the accuracy of the diagnosis. The implementation of a special class of deep leaning 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 restorative dentistry applications.

Since precise data interpretation is important in dental diagnosis, the standardization and benchmarking of data sets might increase the accuracy of AI models in diagnosing dental caries and vertical root fracture or predicting failures of dental restorations. The availability of open data sets will facilitate the development of AI models.

CONCLUSIONS

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

1. The use of AI models to diagnose dental caries and vertical tooth fracture, detect the tooth finishing line, and predict restoration failure has grown substantially since 2019.
2. AI models may provide a powerful tool to assist in the diagnosis of dental caries and vertical tooth fracture, the detection of the tooth finishing line, and the prediction of restoration failure.
3. The dental applications of AI models are still under development. Further studies are required to assess the clinical performance of AI models in restorative dentistry.

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Noteworthy Abstracts of the Current Literature

Esthetic outcomes of implant-supported single crowns related to abutment type and material: A systematic review

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Purpose. To systematically review the influence of abutment material and configuration on the soft tissue esthetic outcomes of implant-supported single crowns (iSCs) after 3 years.

Material and methods. An electronic search on MEDLINE (PubMed) from January 2000 to July 2019 was conducted for clinical trials with no language restrictions. The focus question was: In partially edentulous patients with iSCs, does the abutment material (metal vs ceramic) or the configuration (standardized vs customized) have an effect on the soft tissue esthetic outcomes? Randomized controlled trials, controlled clinical trials, and prospective or retrospective case series with at least 10 patients and a minimum of 3 years of follow-up were included. The esthetic outcomes Pink Esthetic Score (PES), PES/White Esthetic Score (WES; ie, modPES), Papilla Index (PI), soft tissue recession, and papilla height change were extracted. Meta-analysis was performed when applicable.

Results. Of the 6,399 titles identified, 27 studies were included. Combined mean PES/modPES scores, translated into a scale of 0 to 100, were 68.8 for ceramic, 74.2 for metal (P=.392), 71.9 for customized, and 71.3 for standard (P=.981) abutments. Mean soft tissue recession was also similar between the abutment groups, abutment material (P=.850), and configuration (P=.849), ranging from -1.09 mm to +0.59 mm gain. Papilla height changes ranged from -1.22 mm to +1.0 mm gain. The reported mean PI was 2.16 for customized, 2.06 for standard (P=.552), 2.01 for ceramic, and 2.28 for metallic (P=.04) abutments.

Conclusions. This systematic review showed that the abutment material and configuration had minimal impact on the evaluated soft tissue esthetic outcomes. Future research focusing on the included parameters in a randomized controlled manner is needed to validate the present findings.

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