OPEN ACCESS

Saudi Journal of Nursing and Health Care

Abbreviated Key Title: Saudi J Nurs Health Care
ISSN 2616-7921 (Print) |ISSN 2616-6186 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Review Article

The Effects Artificial Intelligence Applications in Prosthodontics Treatment: A Systematic Review

Ahmed M. Elmarakby[1]*, Nouf Yahya Al-Gasem[2], Eman Abdullah M. Mahnashi[3], Zahra Hassan Hakami[4], Turki Adil Alghaith[5], Jassem Abdullah Jassem Almubarak[6], Reema Abdulkader Azzeem[7], Ferial Hamed Almokayad[8], Ali Yassin Alameri[9], Dalal Jumah Alturaif[10]

[1]Associate Professor, Department of Restorative and Prosthetic Dental Sciences, College of Dentistry, Dar Al Uloom University, Riyadh 13313, Saudi Arabia; Associate Professor, Department of Operative Dentistry, Faculty of Dental Medicine, Al-Azhar University, Assiut Branch, Assiut 71524, Egypt
[2]Ajwan Medical Beauty Company, Saudi Arabia; College of Dentistry, Qassim University, Al-Qassim, Saudi Arabia.
[3]General Dentist, College of Dentistry, Jazan University, Jazan, Saudi Arabia
[4]General Dentist, College of Dentistry, Jazan University, Jazan, Saudi Arabia
[5]General Dentist, Al Meswak Dental Clinic, Saudi Arabia; King Abdulaziz University, Jeddah, Saudi Arabia
[6]Al-Ahsa Health Cluster, Al-Ahsa, Saudi Arabia; King Saud University, Riyadh, Saudi Arabia
[7]General Dentist, King Salman Armed Forces Hospital, Saudi Arabia; Ibn Sina National College for Medical Studies, Jeddah, Saudi Arabia
[8]General Dentist, Safwat Al Muhaidib Dental Clinic, Al-Zulfi, Saudi Arabia; Al Mustaqbal University
[0]Consultant in Restorative Dentistry, South Al-Qunfudhah Hospital, Ministry of Health, Al-Qunfudhah, Saudi Arabia
[10]General Dentist, Private Dental Clinic, Saudi Arabia; Al-Farabi College, Saudi Arabia

DOI: https://doi.org/10.36348/sjnhc.2026.v09i11.005 | **Received:** 26.09.2026 | **Accepted:** 20.11.2026 | **Published:** 24.11.2026

***Corresponding author:** Ahmed M. Elmarakby
Associate Professor, Department of Restorative and Prosthetic Dental Sciences, College of Dentistry, Dar Al Uloom University, Riyadh 13313, Saudi Arabia; Associate Professor, Department of Operative Dentistry, Faculty of Dental Medicine, Al-Azhar University, Assiut Branch, Assiut 71524, Egypt

Abstract

Background: Artificial intelligence (AI) is increasingly being integrated into prosthodontics, with potential applications in prosthesis design, treatment planning, fabrication, implant placement, esthetic assessment, and prediction of prosthodontic outcomes. However, the available evidence is heterogeneous, and the clinical applicability of these technologies remains incompletely established. ***Objective:*** This systematic review aimed to evaluate the current evidence regarding the application and performance of artificial intelligence in prosthodontics and to summarize its potential clinical applications, performance characteristics, and limitations. ***Methods:*** A systematic literature search was conducted in PubMed/MEDLINE, ScienceDirect, the Cochrane Library, and Google Scholar. Studies evaluating AI-based methods, including machine learning, deep learning, artificial neural networks, convolutional neural networks, generative models, case-based reasoning, and large language models, in a prosthodontic context were eligible. Clinical, experimental, and computational studies with a direct prosthodontic application were considered. Study selection and reporting followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Methodological quality was assessed using study-design–appropriate appraisal approaches. ***Results:*** The search identified 3,279 records, of which 475 duplicates were removed. After title and abstract screening, 114 reports were sought for retrieval and 71 were assessed for eligibility. Ultimately, 14 studies published between 2015 and 2026 were included. AI applications encompassed removable partial denture design, complete denture fabrication and treatment planning, crown design and outcome prediction, occlusal surface reconstruction, implant planning and guided surgery, tooth-shade and prosthetic color assessment, and maxillofacial prosthesis coloration. Several studies demonstrated high technical performance, including 98.5% accuracy and an area under the curve of 0.998 for crown debonding prediction and up to 97.93% accuracy for tooth-shade classification. AI-assisted implant planning generally produced clinically acceptable plans comparable with human planning while substantially reducing planning time. However, most studies were characterized by small clinical samples, experimental or retrospective designs, limited external validation, and considerable methodological heterogeneity. ***Conclusion:*** Artificial intelligence demonstrates considerable potential as a supportive technology across multiple areas of prosthodontics, particularly implant planning, prosthesis design, esthetic assessment, and prediction of prosthetic

complications. Current evidence suggests that AI can improve efficiency, consistency, and technical performance in selected applications. Nevertheless, the evidence remains insufficient to support replacement of clinician judgment with AI systems. Larger prospective multicenter studies with standardized outcomes, independent external validation, and clinically relevant comparisons are required to establish the reliability, generalizability, and long-term clinical effectiveness of AI in prosthodontic practice.

Keywords: Artificial Intelligence, Prosthodontics, Machine Learning, Deep Learning, Convolutional Neural Networks, Artificial Neural Networks, Large Language Models, Digital Dentistry.

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution **4.0 International License (CC BY-NC 4.0)** which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

INTRODUCTION

Artificial intelligence (AI) has rapidly emerged as a transformative force in healthcare, and prosthodontics is no exception. The discipline of prosthodontics—encompassing the diagnosis, treatment planning, and rehabilitation of missing or deficient oral and maxillofacial structures—has historically relied on clinician expertise, manual laboratory workflows, and subjective esthetic judgment. The integration of AI-driven technologies, including machine learning, deep learning, and generative models, is reshaping these workflows by introducing automation, enhanced diagnostic accuracy, and personalized treatment design [1]. As the volume of research in this domain expands exponentially, a critical synthesis of evidence is essential to understand both the promise and the limitations of AI applications in prosthodontic care.

The foundational strength of AI in prosthodontics lies in its capacity for image analysis and pattern recognition. Systematic reviews and meta-analyses have demonstrated that AI algorithms achieve pooled diagnostic accuracy ranging from 82% to 95% across dental specialties, with convolutional neural networks (CNNs) reaching a pooled accuracy of 93.1% for various diagnostic tasks [2]. In implant dentistry, deep learning models have been developed for the detection and numbering of dental implants on panoramic radiographs, achieving F1-scores exceeding 0.91 and offering the potential to reduce clinicians' workload while improving diagnostic consistency [3]. Notably, a recent in vitro comparative study found that a multiclass AI model outperformed human assessors in differentiating between original and generic dental implants from radiographs, suggesting that AI-based implant identification software may serve as a valuable diagnostic support tool when documentation is incomplete [4].

Beyond diagnosis, AI has demonstrated considerable utility in treatment planning and prosthetic design. Large language models such as ChatGPT 4o have shown high accuracy (97.08%) for simple fixed prosthodontic cases, though performance declined substantially for complex clinical scenarios (19.69%), underscoring the continuing necessity of clinician expertise in intricate treatment planning [5]. In the domain of digital design, AI-powered CAD software has been evaluated for finish line detection and restoration contour design, with one fully automated system achieving acceptability scores comparable to those of dental laboratory technicians and significantly lower deviation metrics [6]. Automated systems have also been developed for complete denture metal base design, with the CDMB-SegNet framework achieving over 98% accuracy and reducing design time to approximately one-tenth of conventional methods [7]. Furthermore, transformer-based and generative deep learning models are now being applied to reconstruct missing tooth morphology and generate three-dimensional tooth shapes, with studies demonstrating high fidelity and dimensional consistency for single-tooth reconstruction across multiple tooth positions [8,9].

The scope of AI in prosthodontics extends beyond conventional restorative workflows into maxillofacial rehabilitation and emerging areas of clinical application. A scoping review of AI in maxillofacial prosthodontics identified applications spanning implant-supported auricular prosthesis production, maxillofacial prosthesis coloration, assessment of lip symmetry in cleft patients, and three-dimensional impression capture of cleft palates [10]. In implantology, AI-powered segmentation of bifid mandibular canals on cone-beam computed tomography has been explored to enhance preoperative safety, though the technique remains supplementary to clinician assessment pending further validation [11]. Despite this rapid expansion, significant gaps and challenges persist. The current evidence base is characterized by methodological heterogeneity, limited sample sizes, and a scarcity of external validation studies, which constrain the generalizability of reported performance metrics [2,12]. Clinical validation in real-world settings remains necessary before routine implementation of many AI tools [4]. Ethical considerations, including algorithmic bias and the appropriate scope of AI-assisted decision-making, require ongoing attention as these technologies mature [13]. The available literature suggests that AI in prosthodontics is at a pivotal juncture: technically capable in controlled settings, yet not fully validated for the complexity and variability of routine clinical practice.

This systematic review aims to synthesize the current evidence on AI applications in prosthodontic treatment, spanning diagnostic imaging, treatment planning, prosthetic design, and maxillofacial rehabilitation. By critically examining both the demonstrated capabilities and the identified limitations, this article seeks to provide a balanced assessment of how AI is currently reshaping prosthodontic workflows

and what remains necessary before widespread clinical adoption can be responsibly achieved.

METHODS

Study Design and Reporting Guidelines

This systematic review was conducted to evaluate the current evidence regarding the application of AI in prosthodontics, including its use in diagnosis, treatment planning, prosthesis design and fabrication, implant planning, esthetic assessment, treatment monitoring, and prediction of prosthodontic treatment outcomes. The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [14]. The methodology was established before the final study selection and was applied consistently throughout the literature search, screening, data extraction, and synthesis processes.

Eligibility Criteria

Studies were considered eligible when they investigated the application of an artificial intelligence-based method, including machine learning, deep learning, artificial neural networks, convolutional neural networks, generative models, case-based reasoning systems, or large language models, in a prosthodontic context. Eligible studies included applications involving fixed prosthodontics, removable prosthodontics, complete dentures, implant-supported prosthodontic treatment, maxillofacial prostheses, prosthesis design or fabrication, tooth morphology reconstruction, esthetic or shade assessment, treatment planning, and prediction of prosthodontic outcomes or complications.

Both clinical and experimental studies were considered when the investigated AI system had a direct or clearly defined application to prosthodontic care, prosthesis design, fabrication, planning, or evaluation. Studies using patient-derived clinical records, intraoral scans, cone-beam computed tomography images, digital dental casts, clinical prostheses, or patient-derived anatomical data were eligible. Laboratory and computational studies were also considered when they directly addressed a prosthodontic application and provided quantitative evaluation of AI performance.

Studies were excluded when AI was used solely for non-prosthodontic dental applications, when the primary outcome concerned dental education rather than prosthodontic performance, or when the study did not evaluate an AI-based method. General restorative dentistry studies without a sufficiently defined prosthodontic application were excluded. Studies based entirely on synthetic or theoretical datasets were not considered part of the clinical evidence base. Review articles, systematic reviews, narrative reviews, editorials, letters, conference abstracts without sufficient methodological information, and other non-original publications were excluded. Duplicate publications reporting the same dataset or study were also excluded.

Information Sources and Literature Search

A comprehensive literature search was conducted in four electronic databases: PubMed/MEDLINE, ScienceDirect, the Cochrane Library, and Google Scholar. The search strategy was developed using combinations of terms related to artificial intelligence and prosthodontics. Search terms included controlled vocabulary, where applicable, and free-text terms related to artificial intelligence, machine learning, deep learning, neural networks, generative artificial intelligence, large language models, prosthodontics, dental prostheses, dentures, crowns, dental implants, implant prosthodontics, and maxillofacial prostheses. Boolean operators “AND” and “OR” were used to combine the search concepts. The database-specific search strategies are presented in Appendix Table S1.

Additional potentially eligible studies were identified by manually screening the reference lists of included studies and relevant review articles. The search was designed to identify original studies evaluating the application or performance of artificial intelligence in prosthodontic diagnosis, treatment planning, prosthesis design or fabrication, implant planning, esthetic assessment, treatment monitoring, and prediction of prosthodontic outcomes.

Study Selection

All retrieved records were screened for eligibility in a sequential process. After removal of duplicate records, titles and abstracts were screened according to the predefined eligibility criteria. Potentially relevant articles were subsequently retrieved in full text and assessed for final inclusion.

Full-text assessment focused on the study population or data source, the nature of the AI intervention, its relationship to prosthodontic care, and the reported outcomes. Studies that did not meet the predefined criteria were excluded, and the reasons for exclusion at the full-text stage were documented. The complete study identification, screening, eligibility assessment, and inclusion process is summarized in the PRISMA flow diagram (Figure 1).

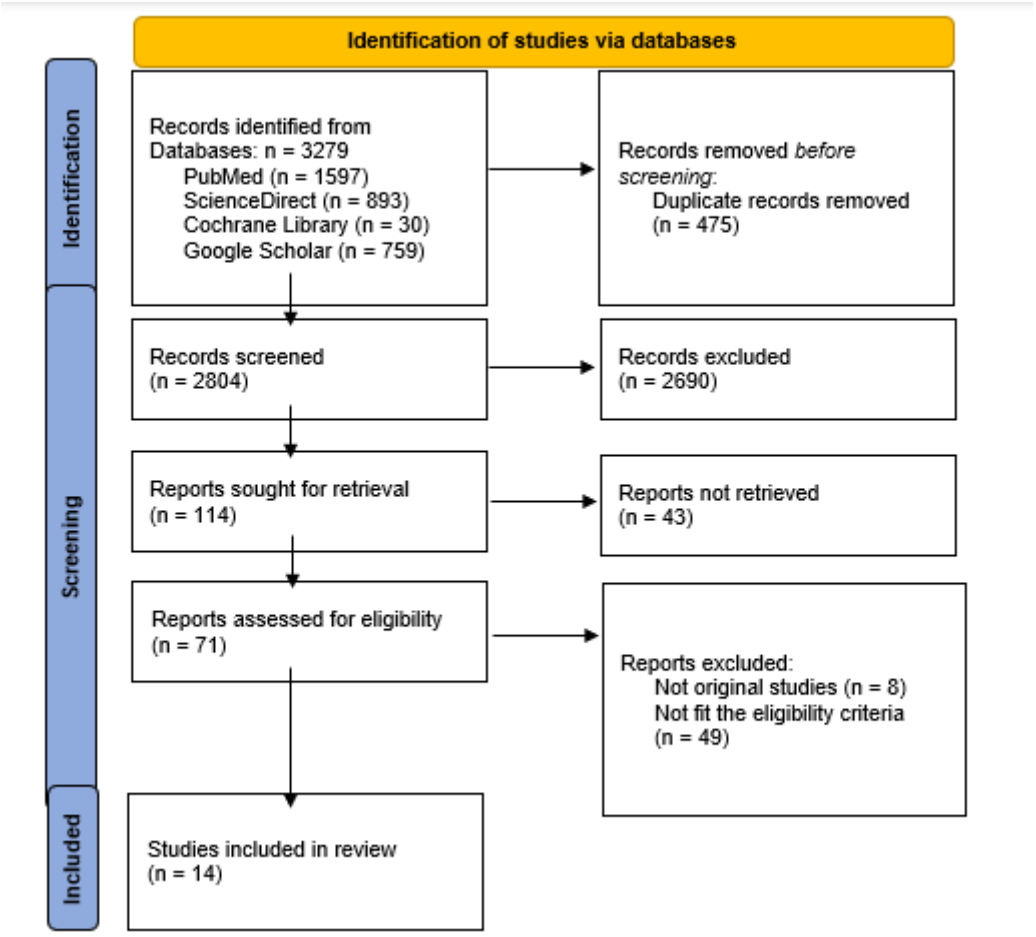


Figure 1: PRISMA flowchart showing the study selection process.

Data Extraction

Data were extracted systematically from all included studies using a predefined data extraction framework. The extracted information included the author and year of publication, study design, prosthodontic application, study population or data source, sample size or dataset size, type of AI technology, comparator where applicable, clinical or experimental setting, outcomes assessed, and principal findings.

For studies evaluating AI performance against human clinicians or conventional approaches, comparative outcomes such as accuracy, precision, recall, area under the receiver operating characteristic curve, geometric deviation, treatment-planning time, clinical acceptability, and morphological or esthetic agreement were recorded when available. For prosthesis-design and fabrication studies, outcomes related to morphology, occlusal characteristics, dimensional accuracy, mechanical performance, color matching, and prosthesis-related clinical parameters were extracted.

Classification of Artificial Intelligence Applications

The included studies were categorized according to the principal prosthodontic application of the AI system. The major categories included removable prosthodontic design, complete denture fabrication and tooth arrangement, fixed prosthodontic design and outcome prediction, implant planning and guided implant surgery, prosthesis and tooth morphology reconstruction, esthetic and color assessment, and maxillofacial prosthesis coloration.

AI technologies were also classified according to their underlying computational approach, including conventional machine learning, artificial neural networks, convolutional neural networks, deep learning, generative adversarial networks, case-based reasoning, and large language models. This classification allowed comparison of the different technological approaches despite substantial differences in study design and outcome measures.

Assessment of Study Quality and Risk of Bias

The methodological quality and risk of bias of the included studies were assessed according to the characteristics and design of each study. Particular consideration was given to the study population or dataset, sample size, representativeness of the data, AI model development and validation procedures, presence and appropriateness of comparator groups, outcome assessment, reporting of performance measures, and potential sources of bias.

For studies involving clinical participants, attention was given to participant selection, prospective or retrospective data collection, completeness of follow-up, and the objectivity and reproducibility of outcome assessment. For experimental and computational studies, the assessment focused on dataset construction, training and testing procedures, separation of training and validation data, external validation where available, and the risk of overfitting or limited generalizability. Because the included studies differed substantially in design and methodological characteristics, the risk-of-bias assessment was interpreted in the context of each study type rather than applying a single clinical risk-of-bias instrument uniformly to all studies.

Outcome Measures

The primary outcomes were the reported performance and clinical applicability of AI systems in prosthodontics. These included diagnostic or classification accuracy, precision, recall, F-measure, area under the curve, agreement with expert or conventional planning, geometric accuracy, dimensional deviation, treatment-planning time, prosthesis morphology, occlusal characteristics, esthetic outcomes, and clinical acceptability. Secondary outcomes included consistency and reproducibility of AI-generated outputs, computational efficiency, comparison with human performance, and the potential integration of AI into digital prosthodontic workflows.

Data Synthesis

Because of substantial heterogeneity among the included studies in terms of study design, AI technologies, datasets, prosthodontic applications, comparators, and outcome measures, a quantitative meta-analysis was not considered appropriate. The findings were therefore synthesized narratively.

Studies were grouped according to their principal prosthodontic application and AI methodology. Quantitative performance measures were reported descriptively where available, while comparisons between AI-based and conventional or human approaches were summarized according to the outcomes reported in the individual studies. Greater emphasis was placed on studies involving actual patients or patient-derived clinical data, while findings from laboratory, experimental, and computational studies were interpreted as supportive evidence regarding technical feasibility rather than definitive evidence of clinical effectiveness.

Quality Assessment

The methodological quality of the 14 included studies was assessed using study-design–appropriate appraisal approaches to account for the substantial heterogeneity in study methodology and clinical application of artificial intelligence. Experimental and computational studies were assessed using the Joanna Briggs Institute (JBI) critical appraisal approach, while prediction and AI-based predictive modeling studies were evaluated using PROBAST. Comparative clinical studies were assessed using the Methodological Index for Non-Randomized Studies (MINORS), and clinical case-series studies were evaluated using the JBI Critical Appraisal Checklist for Case Series. For studies involving AI-based imaging applications, relevant AI-specific reporting and methodological criteria based on CLAIM were also considered. Overall, the included studies demonstrated moderate to high methodological quality. The comparative clinical studies evaluating AI-assisted implant planning generally demonstrated stronger methodological characteristics, whereas studies with small experimental or case-series samples were limited primarily by small sample sizes, lack of external validation, and absence of control groups. A detailed summary of the methodological quality assessment, including the appraisal tool and major strengths and limitations of each study, is presented in **Table 1**.

Table 1: Methodological quality assessment of the included studies, including study design, artificial intelligence application, appraisal tool, methodological strengths and limitations, and overall quality judgment

Study	Tool used	Main methodological strengths	Main limitations	Overall judgment
Li *et al.,* [15]	JBI Experimental	Defined AI model and comparative performance assessment	Experimental computational design; limited clinical validation	Moderate
Cheng *et al.,* [16]	PROBAST	Patient-derived data and quantitative prediction assessment	Limited external/independent validation	Moderate
Chen *et al.,* [17]	Prediction/decision-support appraisal	Clearly defined clinical decision-support framework and performance metrics	Limited prospective clinical validation	Moderate
Mine *et al.,* [18]	JBI Experimental	Defined experimental protocol and quantitative color assessment	Small validation sample	Moderate

Study	Tool used	Main methodological strengths	Main limitations	Overall judgment
Yamaguchi *et al.,* [19]	PROBAST	Large image dataset and strong predictive performance	Retrospective dataset; limited external validation	Moderate–High
Tian *et al.,* [20]	AI methodological appraisal/CLAIM	Large patient-derived dataset and quantitative reconstruction assessment	Computational/experimental design without clinical outcome validation	Moderate
Ding *et al.,* [21]	AI methodological appraisal/CLAIM	Comparative morphology and mechanical evaluation	Limited clinical validation	Moderate
Elgarba *et al.,* [22]	MINORS + CLAIM	Direct AI–human comparison and clinically relevant planning outcomes	Small sample size and non-randomized design	High
Elgarba *et al.,* [23]	MINORS + CLAIM	Independent comparative validation and standardized datasets	Preclinical design and limited clinical outcome assessment	High
Elgarba *et al.,* [24]	MINORS + CLAIM	Clinical validation against human planning and actual implant placement	Small clinical sample and non-randomized design	High
Shalash & Zohnee [25]	JBI Case Series	Clinical application with quantitative implant-placement outcomes	Small case-series sample and no control group	Moderate
Karcioglu *et al.,* [26]	JBI Experimental	Multiple ML algorithms and repeated measurements under different lighting conditions	Experimental image-based evaluation without clinical validation	Moderate
Alageel [27]	JBI Experimental	Multiple LLMs compared with expert assessment and reference design	Small number of clinical scenarios; AI outputs may be model/version dependent	Moderate
Choi *et al.,* [28]	JBI Case Series	Within-patient comparison using objective occlusal and esthetic outcomes	Very small sample and preliminary case-series design	Moderate

RESULTS

The initial database search identified 3,279 records, including 1,597 from PubMed/MEDLINE, 893 from ScienceDirect, 30 from the Cochrane Library, and 759 from Google Scholar. Following the removal of 475 duplicate records, 2,804 records underwent title and abstract screening, of which 2,690 were excluded. A total of 114 reports were subsequently sought for retrieval; 43 reports could not be retrieved, leaving 71 full-text reports for eligibility assessment. Of these, 57 reports were excluded, including 8 that were not original studies and 49 that did not meet the predefined eligibility criteria. Ultimately, 14 studies met all eligibility criteria and were included in the systematic review.

Characteristics of the Included Studies

A total of 14 studies were included in the systematic review, published between 2015 and 2026. The included studies demonstrated substantial heterogeneity in terms of prosthodontic application, AI methodology, study design, data source, and outcome assessment. The studies investigated AI applications across removable prosthodontics, fixed prosthodontics, complete denture therapy, implant dentistry, maxillofacial prosthetics, and esthetic prosthodontic procedures. Summary characteristics of included studies are shown in Table 1.

Study	Year	Prosthodontic application	Study design / data source	AI technique	Sample / dataset	Main outcomes assessed	Main findings
Li *et al.*, [15]	2015	Computerized color matching of ceramic dental restorations	Experimental / computational study	Genetic algorithm–optimized back-propagation neural network (GA+BP)	Dental color-matching experimental data	Color-matching accuracy and prediction robustness	GA+BP improved the precision and robustness of computerized color matching compared with conventional BP-based approaches.
Cheng *et al.*, [16]	2015	Complete denture treatment planning; prediction of facial changes	Patient-based retrospective/experimental modeling study	BP neural network combined with Laplacian deformation	48 edentulous patients, pre- and postoperative 3D facial models	Prediction of postoperative facial soft-tissue deformation	The neural network successfully predicted facial deformation after complete denture treatment and demonstrated feasibility for digital denture design and tooth arrangement.
Chen *et al.*, [17]	2016	Removable partial denture (RPD) design	Clinical decision-support/model validation study	Ontology-driven case-based reasoning with cosine similarity	104 patients	Agreement of AI-generated RPD designs with professional designs; precision, MAP, NDCG, AUC	The system demonstrated efficient retrieval and generation of RPD designs, with high precision and good agreement with professional designs.
Mine *et al.*, [18]	2019	Maxillofacial prosthesis coloration	Experimental laboratory validation	Deep artificial neural network (ANN)	52 silicone elastomer specimens; validation using skin color from 5 participants	Color difference (CIEDE00) between simulated prosthesis and skin	ANN produced lower color differences than random forest (3.45 ± 0.87 vs 5.54 ± 1.41), indicating superior color-matching performance.
Yamaguchi *et al.*, [19]	2019	CAD/CAM composite resin crown failure prediction	Retrospective patient-derived dataset	Convolutional neural network (CNN) / deep learning	24 clinical crown cases: 12 trouble-free and 12 debonding; 8,640 images	Prediction accuracy, precision, recall, F-measure, AUC	CNN achieved 98.5% accuracy, 97.0% precision, 100% recall, F-measure 0.985 and AUC 0.998 for predicting

Study	Year	Prosthodontic application	Study design / data source	AI technique	Sample / dataset	Main outcomes assessed	Main findings
							crown debonding.
Tian *et al.*, [20]	2022	Dental crown/occlusal surface reconstruction	Patient-derived digital dental data	Dual-discriminator adversarial learning network with dilated convolutional generator	1,000 real-world patient dental samples	Reconstruction accuracy and morphological similarity	Generated occlusal surfaces showed anatomically reasonable morphology with an RMS error of approximately 0.114 mm and outperformed comparison methods.
Ding *et al.*, [21]	2023	Automated personalized dental crown design	Digital cast experimental study	3D Deep Convolutional Generative Adversarial Network (3D-DCGAN)	600 digital casts for training; 12 test datasets	3D morphological similarity, cusp angle, occlusal contacts and simulated mechanical performance	3D-DCGAN generated crowns with morphology closely matching natural teeth and favorable simulated stress distribution and fatigue performance.
Elgarba *et al.*, [22]	2024	Automated virtual implant placement	Comparative validation study using CBCT + intraoral scans	AI-driven automated implant planning	10 cases involving single posterior mandibular tooth replacement	Planning quality, clinical acceptability, planning time and consistency	AI plans were clinically acceptable in approximately 95% of assessments and were substantially faster than human planning (198 ± 33 vs 435 ± 92 s).
Elgarba *et al.*, [23]	2025	Presurgical implant planning / virtual implant placement	Preclinical comparative validation	AI-based automated implant planning	50 CBCT + intraoral scan datasets	Implant position, dimensions, clinical acceptability, time and consistency	Approximately 89% of AI plans vs 93% of human plans were clinically acceptable. AI planning was more than twice as fast and showed greater consistency.
Elgarba *et al.*, [24]	2025	AI-assisted implant planning compared with actual implant placement	Clinical validation study	AI-driven automated virtual implant placement	32 patients with posterior mandibular single-implant treatment	Angular/linear deviation, implant dimensions, planning time and consistency	AI planning showed no significant differences from human planning/actual placement for major positioning

Study	Year	Prosthodontic application	Study design / data source	AI technique	Sample / dataset	Main outcomes assessed	Main findings
							parameters and was approximately 10-fold faster than human planning.
Shalash & Zohnee [25]	2025	Full-arch implant rehabilitation and surgical guide design	Prospective clinical study	AI-assisted automatic CBCT bone segmentation and digital planning	10 patients; 80 implants	Platform and apical deviation, angular deviation, accuracy of implant placement	Mean global deviation was 1.24 mm at the platform, 1.29 mm at the apex, and mean angular deviation was 3.63°; deviations were considered clinically acceptable.
Karciog lu *et al.*, [26]	2025	Prosthetic tooth shade assessment	Experimental image-based study	Machine-learning classification algorithms	580 dental images, 29 Vita shade classes under 4 lighting conditions	Shade classification accuracy and robustness to different lighting	ML achieved up to 97.93% accuracy in identifying 29 tooth shades independent of clinical lighting conditions.
Alageel [27]	2026	Removable partial denture design	Comparative AI evaluation using standardized clinical scenarios	Large language models: ChatGPT, Copilot, Gemini and DeepSeek; comparison with AiDENTAL	25 partially edentulous clinical scenarios, evaluated by 6 blinded experts	RPD design quality, accuracy, consistency and predicted retention	Copilot and Gemini produced the most consistent AI-generated RPD designs. AiDENTAL achieved the highest overall design quality, followed by Copilot.
Choi *et al.*, [28]	2026	Complete denture fabrication and tooth arrangement	Preliminary within-patient clinical case series	AI-assisted digital complete denture workflow	6 completely edentulous patients, each receiving AI-assisted and conventiona l dentures	Occlusal force distribution, balanced contacts, facial midline, nasolabial angle and arch dimensions	Both workflows were clinically feasible. No significant difference in occlusal force imbalance was observed, while AI-assisted dentures showed differences in facial midline, nasolabial angle and arch dimensions.

Two studies investigated AI-assisted removable partial denture (RPD) design. Chen *et al.,* [17] developed an ontology-driven, case-based clinical decision-support system and evaluated its RPD designs against professional designs in 104 patients. The model demonstrated favorable retrieval performance, with a precision of 0.67 at position 5, a maximum precision of 0.96, a mean average precision of 0.61, and a normalized discounted cumulative gain of 0.74. More recently, Alageel [27] evaluated four large language models (ChatGPT, Copilot, Gemini, and DeepSeek) using 25 partially edentulous clinical scenarios based on Kennedy classifications. The AI-generated designs were compared with AiDENTAL reference designs and evaluations from six blinded experts. Copilot and Gemini demonstrated the most consistent and accurate outputs among the evaluated large language models, whereas AiDENTAL achieved the highest overall design quality.

Two studies focused on complete denture applications. Cheng *et al.,* [16] used a back-propagation neural network to predict facial soft-tissue deformation following complete denture treatment using preoperative and postoperative three-dimensional facial models from 48 edentulous patients. The proposed model demonstrated the feasibility of predicting postoperative facial deformation and was intended to provide constraints for digital tooth arrangement and complete denture design. In a more recent preliminary clinical case series, Choi *et al.,* [28] evaluated an AI-assisted complete denture workflow in six completely edentulous patients. Each patient received both an AI-assisted and a conventionally arranged complete denture using the same definitive impressions and jaw-relation records. Both approaches demonstrated balanced occlusal contacts in all participants, and no statistically significant difference was observed in occlusal force imbalance. However, differences were observed in facial-maxillary midline discrepancy, nasolabial angle, and maxillary arch dimensions.

Several studies evaluated AI for fixed prosthodontic procedures, particularly crown design, occlusal reconstruction, and restoration prognosis. Yamaguchi *et al.,* [19] developed a convolutional neural network to predict debonding of CAD/CAM composite resin crowns using 24 clinical cases, comprising 12 trouble-free and 12 debonding cases. The model achieved an accuracy of 98.5%, precision of 97.0%, recall of 100%, an F-measure of 0.985, and an area under the receiver operating characteristic curve of 0.998. Tian *et al.,* [20] developed a dual-discriminator adversarial learning framework for dental occlusal surface reconstruction and evaluated it using 1,000 real-world patient dental samples. The generated occlusal surfaces demonstrated anatomically reasonable morphology, with a reported root-mean-square error of approximately 0.114 mm. Ding *et al.,* [21] applied a three-dimensional deep convolutional generative adversarial network (3D-DCGAN) to the automated design of dental crowns. The model was trained using 600 digital casts and evaluated using 12 test datasets. The AI-generated crowns demonstrated close morphological similarity to natural teeth and favorable simulated mechanical performance, including stress distribution and fatigue behavior.

Four studies investigated AI-assisted implant planning or implant surgery. Elgarba *et al.,* [24] evaluated an automated AI-based virtual implant placement system using 10 CBCT and intraoral scan datasets. Approximately 95% of AI-generated plans were considered to require no major clinically relevant correction, compared with 96% for human-generated plans. AI planning was also substantially faster than human planning, requiring approximately 198 ± 33 seconds compared with 435 ± 92 seconds. A subsequent preclinical validation study by the same research group evaluated 50 CBCT and intraoral scan datasets and found that approximately 89% of AI-generated plans and 93% of human-generated plans were considered clinically acceptable [23]. AI planning was more than twice as fast and demonstrated greater consistency. A further clinical validation study involving 32 patients compared AI-driven virtual planning with human planning and actual implant placement [22]. No statistically significant differences were identified for the major implant positioning parameters, while AI planning was approximately ten times faster than human planning. Shalash and Zohnee [25] evaluated an AI-assisted workflow for full-arch implant rehabilitation in 10 patients receiving a total of 80 implants. AI-assisted automatic bone segmentation and surgical guide design resulted in mean global deviations of 1.24 mm at the implant platform and 1.29 mm at the apex, with a mean angular deviation of 3.63°, which the authors considered clinically acceptable.

AI was also applied to esthetic and maxillofacial prosthodontic procedures. Mine *et al.,* [18] evaluated a deep artificial neural network for coloration of maxillofacial prostheses using 52 silicone elastomer specimens, with validation against the skin color of five participants. The ANN produced a mean CIEDE00 color difference of 3.45 ± 0.87 compared with 5.54 ± 1.41 for the random forest algorithm, indicating superior color-matching performance. Li *et al.,* [15] developed a genetic algorithm-optimized back-propagation neural network for computerized color matching of dental restorations. The GA+BP approach demonstrated improved color-matching precision and prediction robustness compared with conventional approaches. Karcioglu *et al.,* [26] subsequently evaluated six machine-learning algorithms for tooth-shade classification using 580 dental images representing 29 Vita shade values captured under different clinical lighting conditions. The best-performing approach achieved an accuracy of 97.93% and demonstrated the ability to classify tooth shades with reduced dependence on the clinical light source.

DISCUSSION

This systematic review synthesized evidence from 14 studies published between 2015 and 2026, demonstrating that AI applications in prosthodontics have expanded across diagnostic imaging, treatment planning, prosthesis design, and outcome prediction. The findings reveal a consistent pattern: AI systems demonstrate high technical performance in controlled settings, particularly in implant planning, crown design, and shade assessment, but the evidence base remains characterized by methodological heterogeneity and limited clinical validation. These observations align with broader assessments of AI in dentistry, where pooled diagnostic accuracy ranges from 82% to 95% across specialties, yet substantial heterogeneity (I^2 >75%) persists across performance metrics [2].

The strongest clinical evidence in this review emerged from AI-assisted implant planning. Elgarba *et al.,* demonstrated that AI-generated implant plans were clinically acceptable in approximately 89-95% of cases, with planning times reduced to approximately one-tenth of human planning duration [22–24]. These findings are corroborated by an umbrella review of AI in implant dentistry, which reported that deep learning models, particularly convolutional neural networks, achieved accuracy exceeding 90% for implant identification, planning, and success prediction [29]. The clinical relevance of these findings is underscored by a meta-analysis demonstrating that AI-based radiographic assessment for marginal bone loss around implants achieved a pooled sensitivity of 0.84 and specificity of 0.91, significantly outperforming dentists in specificity (P<.001) [30]. However, the absence of long-term clinical outcome data—such as implant survival rates or prosthetic complication rates—limits the translation of these technical successes into evidence of improved patient outcomes.

The application of AI to prosthesis design represents a domain where computational approaches have demonstrated particular promise. In this review, Tian *et al.,* [20] achieved occlusal surface reconstruction with root-mean-square error of approximately 0.114 mm using a dual-discriminator adversarial learning framework , while Ding *et al.,* [21] demonstrated that 3D-DCGAN-generated crowns exhibited favorable morphological similarity and simulated mechanical performance. These technical achievements align with systematic review evidence indicating that deep learning applications in prosthodontics are concentrated in prosthesis design and manufacturing (13 of 31 studies), with generative models as the predominant task type and convolutional neural networks as the most utilized architecture [31]. The reported Intersection over Union values ranging from 60% to 90% across included studies suggest substantial but variable design accuracy [31].

However, the clinical translation of these design capabilities requires careful interpretation. A narrative review of AI in removable prosthodontics identified 15 relevant studies, with AI-based applications spanning removable partial denture design, classification of partially edentulous arches, and prediction of prosthodontic treatment outcomes. The review noted that while high accuracy levels were reported, research focus has been predominantly on the diagnostic phase, with few studies addressing treatment planning and implementation. This observation is consistent with the present review's finding that most included studies employed experimental or computational designs rather than prospective clinical validation.

AI-based shade matching emerged as another area of demonstrated technical capability. Karcioglu *et al.,* reported 97.93% accuracy in tooth shade classification using machine learning algorithms across 580 dental images under varying lighting conditions [26], while Li *et al.,* demonstrated improved color-matching precision using a genetic algorithm-optimized backpropagation neural network [30]. These findings resonate with broader evidence indicating that AI systems for dental shade matching have achieved performance levels suitable for clinical application, though the clinical significance of small color differences—often below the perceptibility threshold—requires further investigation [32].

In maxillofacial prosthodontics, Mine *et al.,* [18] demonstrated that deep artificial neural networks achieved mean CIEDE00 color differences of 3.45 ± 0.87 compared with 5.54 ± 1.41 for random forest algorithms. A scoping review of AI in maxillofacial prosthodontics confirmed that AI-driven techniques, including deep learning and generative models, have enhanced the accuracy of facial scanning, three-dimensional modeling, and prosthesis fabrication, with attention-based models outperforming traditional artificial neural networks in predicting pigment combinations [10]. Nevertheless, the review cautioned that clinical validation, cost-effectiveness, and workflow integration remain unresolved challenges.

The emergence of large language models as potential clinical decision-support tools represents a distinct development within prosthodontic AI. Alageel evaluated four LLMs against expert assessments for removable partial denture design, finding that Copilot and Gemini produced the most consistent AI-generated designs, though the specialized AiDENTAL system achieved the highest overall design quality [27]. This pattern mirrors findings from dental licensing examinations, where reasoning-specialized models such as ChatGPT-o1 achieved 80.54% accuracy on prosthodontics questions, contextually comparable to the human average of 79.51%, while Korean-language-optimized models performed substantially worse (34.37%) [33]. These results suggest that architectural sophistication, rather than linguistic optimization, drives clinical performance in domain-specific tasks.

However, systematic review evidence on LLMs in dentistry highlights significant limitations, including lack of scientific references, insufficient accuracy in citation generation, and failure to specify model versions or testing protocols. The observation that ChatGPT-4 shows promise in answering periodontics-related questions with high accuracy, often exceeding human performance, must be tempered by concerns regarding reliability and applicability in professional contexts [34]. These findings underscore that while LLMs demonstrate impressive capabilities in controlled evaluation settings, their integration into clinical prosthodontic workflows requires careful validation and appropriate safeguards.

The methodological quality assessment in this review revealed moderate to high quality for most included studies, with comparative clinical studies evaluating AI-assisted implant planning demonstrating the strongest methodological characteristics. However, a substantial proportion of studies were limited by small sample sizes, experimental or retrospective designs, and absence of external validation. These limitations are consistent with findings from broader assessments of AI in dentistry. A systematic review of AI in prosthodontics using QUADAS-2 found that only 18.3% of included studies were at low risk of bias, while 52.6% and 28.9% were at high and unclear risk, respectively [35]. An umbrella review of AI for dental caries detection similarly concluded that although AI models demonstrate high diagnostic performance under experimental conditions, current evidence does not support their use as stand-alone diagnostic tools, and implementation should be restricted to decision-support contexts [36].

The heterogeneity observed across included studies reflects a broader challenge in AI prosthodontic research: the absence of standardized reporting frameworks, outcome measures, and validation protocols. This variability complicates quantitative synthesis and limits the generalizability of reported performance metrics. A systematic mapping review of artificial neural networks in prosthodontics explicitly noted the difficulty of comparing studies due to inconsistent descriptions of ANN architecture, training methodology, and validation approaches [37]. Furthermore, ethical considerations including data privacy, algorithmic bias, and the potential displacement of clinical judgment have been identified as requiring structured frameworks and professional education before widespread adoption.

The findings of this review support a nuanced position regarding AI in prosthodontics: these technologies demonstrate genuine potential to enhance efficiency, consistency, and technical performance in selected applications, but current evidence does not support the replacement of clinician judgment with autonomous AI systems. The most defensible clinical applications at present involve AI as decision-support tools—particularly in implant planning, where substantial time savings and clinically acceptable accuracy have been demonstrated, and in design optimization, where computational approaches can augment rather than substitute for prosthodontic expertise.

The observation that digital precision should amplify prosthodontic judgment rather than substitute for it reflects an emerging consensus in the field. Future research priorities should include larger prospective multicenter trials with standardized outcome measures, independent external validation of AI models, direct comparisons with established clinical workflows, and assessment of patient-reported outcomes alongside technical performance metrics. The development of specialized reporting guidelines and risk-of-bias tools for AI prosthodontic studies would further strengthen the evidence base and facilitate meaningful synthesis across investigations.

CONCLUSION

Artificial intelligence is emerging as a promising adjunct across multiple domains of prosthodontics, including prosthesis design, occlusal surface reconstruction, tooth shade and color assessment, prediction of prosthetic complications, complete denture fabrication, and implant planning and placement. AI-based approaches generally demonstrated favorable performance, with several studies reporting high predictive accuracy, improved consistency, and substantially reduced planning time compared with conventional or human-based approaches. The strongest clinical evidence was observed in AI-assisted implant planning and placement, where AI-generated plans showed clinically acceptable accuracy and greater efficiency compared with human planning. AI applications in removable partial denture design, complete denture fabrication, prosthetic coloration, and crown design also demonstrated promising results, although much of the available evidence remains experimental or based on small clinical samples. Despite these encouraging findings, the current evidence base remains limited by substantial methodological heterogeneity, small sample sizes, retrospective or experimental designs, limited external validation, and the scarcity of prospective controlled clinical studies. Therefore, the available evidence does not yet support the replacement of clinician judgment with AI-based systems. Instead, AI should currently be considered a supportive technology that may enhance diagnostic consistency, treatment planning, efficiency, and prosthesis fabrication when appropriately validated and integrated into clinical workflows. Future research should prioritize larger multicenter prospective studies, standardized outcome measures, independent external validation, and direct comparisons with established clinical workflows. Such evidence will be essential to determine the generalizability, reliability, clinical

effectiveness, and long-term value of AI in prosthodontic practice.

REFERENCES

1. Schwendicke F, Mohammad Rahimi H, Tichy A: Artificial Intelligence in Prosthodontics. Dent Clin North Am. 2025, 69:315–26. 10.1016/j.cden.2024.11.009
2. Saikia A, Kvist T, Fawzy A, Anthonappa R: Artificial Intelligence in dentistry: an overview of systematic reviews and meta-analysis. Evid Based Dent. 2025, 26:180–180. 10.1038/s41432-025-01190-z
3. Y B, K S, F T, Ma K: Artificial Intelligence-Based Detection and Numbering of Dental Implants on Panoramic Radiographs. Clin Implant Dent Relat Res. 2025, 27:. 10.1111/cid.70000
4. Mk B, Np H, B S, *et al.,*: Radiological differentiation of original and generic dental implants using a multiclass AI model in comparison with human expertise: an in vitro study. J Dent. 2026, 175:. 10.1016/j.jdent.2026.106945
5. Ö İ, K K: Assessing the accuracy, repeatability, and consistency of ChatGPT 4o in treatment planning for tooth-supported fixed prostheses: a comparative analysis of simple and complex clinical cases. Clin Oral Investig. 2025, 29:. 10.1007/s00784-025-06521-z
6. Sawangsri K, Bekkali M, Lutz N, *et al.,*: Acceptability and deviation of finish line detection and restoration contour design in single-unit crown: Comparative evaluation between 2 AI-based CAD software programs and dental laboratory technicians. J Prosthet Dent. 2025, 134:409–17. 10.1016/j.prosdent.2025.03.037
7. Li C, Jin Y, Du Y, *et al.,*: Efficient complete denture metal base design via a dental feature-driven segmentation network. Comput Biol Med. 2024, 175:108550. 10.1016/j.compbiomed.2024.108550
8. Wang Y, Shi Y, Li N, Lin W-S, Tan J, Chen L: Automated reconstruction of missing tooth morphology using a transformer-based implicit neural network: A multi-tooth position evaluation. J Prosthodont Off J Am Coll Prosthodont. 2026, 35:191–200. 10.1111/jopr.70084
9. Chanintonsongkhla C, Chouvatut V, Bunkhumpornpat C, Theerasopon P: A latent variable deep generative model for 3D anterior tooth shape. J Prosthodont Off J Am Coll Prosthodont. 2026, 35:511–9. 10.1111/jopr.14092
10. Aradya A, Sravani K, Ravi MB, *et al.,*: Artificial intelligence for maxillofacial prosthodontics: A technological shift in craniofacial rehabilitation- a scoping review. J Oral Biol Craniofacial Res. 2025, 15:1749–66. 10.1016/j.jobcr.2025.10.006
11. Gumussoy I, Demirezer K, Duman SB, Haylaz E, Bayrakdar IS, Celik O, Syed AZ: AI-powered segmentation of bifid mandibular canals using CBCT. BMC Oral Health. 2025, 25:907. 10.1186/s12903-025-06311-9
12. Inchingolo AD, Marinelli G, Fiore A, *et al.,*: Diagnostic Support in Dentistry Through Artificial Intelligence: A Systematic Review. Bioengineering. 2025, 12:1244. 10.3390/bioengineering12111244
13. Ma Z, Du C, Lao Q, Xie X: Generative Artificial Intelligence: Applications and Future Prospects in Dentistry. Int Dent J. 2026, 76:108276. 10.1016/j.identj.2025.108276
14. Page MJ, McKenzie JE, Bossuyt PM, *et al.,*: The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021, n71. 10.1136/bmj.n71
15. Li H, Lai L, Chen L, Lu C, Cai Q: The Prediction in Computer Color Matching of Dentistry Based on GA+BP Neural Network. Comput Math Methods Med. 2015, 2015:1–7. 10.1155/2015/816719
16. Cheng C, Cheng X, Dai N, Jiang X, Sun Y, Li W: Prediction of facial deformation after complete denture prosthesis using BP neural network. Comput Biol Med. 2015, 66:103–12. 10.1016/j.compbiomed.2015.08.018
17. Chen Q, Wu J, Li S, Lyu P, Wang Y, Li M: An ontology-driven, case-based clinical decision support model for removable partial denture design. Sci Rep. 2016, 6:27855. 10.1038/srep27855
18. Mine Y, Suzuki S, Eguchi T, Murayama T: Applying deep artificial neural network approach to maxillofacial prostheses coloration. J Prosthodont Res. 2020, 64:296–300. 10.1016/j.jpor.2019.08.006
19. Yamaguchi S, Lee C, Karaer O, Ban S, Mine A, Imazato S: Predicting the Debonding of CAD/CAM Composite Resin Crowns with AI. J Dent Res. 2019, 98:1234–8. 10.1177/0022034519867641
20. Tian S, Huang R, Li Z, Fiorenza L, Dai N, Sun Y, Ma H: A Dual Discriminator Adversarial Learning Approach for Dental Occlusal Surface Reconstruction. J Healthc Eng. 2022, 2022:1–14. 10.1155/2022/1933617
21. Ding H, Cui Z, Maghami E, *et al.,*: Morphology and mechanical performance of dental crown designed by 3D-DCGAN. Dent Mater. 2023, 39:320–32. 10.1016/j.dental.2023.02.001
22. Elgarba BM, Fontenele RC, Dawood EA, Lahoud P, Meeus J, Jacobs R: Clinical Feasibility of AI - Driven Automated Virtual Dental Implant Placement: A Cross-Sectional Comparative Study. Clin Implant Dent Relat Res. 2025, 27:e70111. 10.1111/cid.70111
23. Elgarba BM, Fontenele RC, Du X, Mureșanu S, Tarce M, Meeus J, Jacobs R: Artificial Intelligence Versus Human Intelligence in Presurgical Implant Planning: A Preclinical Validation. Clin Oral Implants Res. 2025, 36:835–45. 10.1111/clr.14429
24. Elgarba BM, Fontenele RC, Mangano F, Jacobs R: Novel AI-based automated virtual implant placement: Artificial versus human intelligence. J Dent. 2024, 147:105146. 10.1016/j.jdent.2024.105146
25. Shalash M, Zohnee A: The application of artificial intelligence in full arch computer assisted implant

surgery - A clinical study. Digit Dent J. 2025, 1:100005. 10.1016/j.ddj.2025.100005
26. Karcioglu AA, Efitli E, Simsek E, Ozdogan A, Karatas F, Senocak T: ML-based tooth shade assessment to prevent metamerism in different clinic lights. Lasers Med Sci. 2025, 40:39. 10.1007/s10103-025-04297-y
27. 27. Alageel O: Integration of Artificial Intelligence in Designing Removable Partial Dentures. Int Dent J. 2026, 76:109636. 10.1016/j.identj.2026.109636
28. 28. Choi S-Y, Choi J-W, Choi J-H, Huh J-B: Evaluation of an Artificial Intelligence-Assisted Workflow for Complete Denture Fabrication in Completely Edentulous Patients: A Preliminary Within-Patient Clinical Case Series. Appl Sci. 2026, 16:7112. 10.3390/app16147112
29. Mathur A, Mehta V, Bhadania M, Patil PG: Artificial intelligence in dental implant identifications, planning accuracies, and success predictions: An umbrella review. J Prosthet Dent. 2026, 136:412–21. 10.1016/j.prosdent.2026.05.004
30. Li Y, Wang X, Zhu H, Ye W: The diagnostic performance of AI based on dental radiographs in predicting marginal bone loss around dental implants: A systematic review and meta-analysis. J Prosthet Dent. 2025, 134:2190.e1-2190.e11. 10.1016/j.prosdent.2025.08.021
31. R R, K K, P M, Ts S, Am T, A Z, M R-L: Deep learning applications in prosthodontics: A systematic review. J Prosthet Dent. 2025, 135:539–51. 10.1016/j.prosdent.2025.04.009
32. Jeong J-S, Kim K-S, Gu Y, *et al.,*: Evaluation of VITA shade–based tooth color categories using deep learning. Sci Rep. 2025, 15:40098. 10.1038/s41598-025-23954-4
33. Hlaing NHMM, Park K, Hahn S, Lee SY, Yeo I-SL, Lee J-H: Chain-of-Thought reasoning versus linguistic optimization for artificial intelligence models on the prosthodontics section of a dental licensing examination. J Prosthet Dent. 2026, 135: 394.e1-394.e8. 10.1016/j.prosdent.2025.10.004
34. Alhazmi N, Alshehri A, BaHammam F, Philip M, Nadeem M, Khanagar S: Can Large Language Models Serve as Reliable Tools for Information in Dentistry? A Systematic Review. Int Dent J. 2025, 75:100835. 10.1016/j.identj.2025.04.015
35. Baxmann M, Kárpáti K, Baráth Z: The potentials and challenges of integrating generative artificial intelligence (AI) in dental and orthodontic education: a systematic review. BMC Oral Health. 2025, 25:905. 10.1186/s12903-025-06070-7
36. Bittar A, Dascanio R, Özcan M: Artificial intelligence for dental caries detection: An umbrella review. J Dent. 2026, 175:106944. 10.1016/j.jdent.2026.106944
37. Bobeică O, Iorga D: Artificial neural networks development in prosthodontics - a systematic mapping review. J Dent. 2024, 151:105385. 10.1016/j.jdent.2024.105385