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Artificial Intelligence in Fixed Prosthodontics: A Narrative Review

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ABSTRACT: Artificial intelligence (AI) is being incorporated into fixed prosthodontics through digital workflows for dental shade selection, finish-line detection, restoration design, analysis of static occlusal morphology and contact distribution, imaging interpretation, and material evaluation. This narrative review examines AI applications in fixed prosthodontics, summarises evidence published since January 2010, considers earlier publications where relevant for historical and technical context, and discusses reported performance and limitations relevant to clinical translation. An electronic PubMed search was conducted to identify English-language full-text publications, and reference lists of relevant publications and recent reviews were also screened. The search strategy included terms for dental shade selection and colour matching in addition to fixed-restorative applications. AI-based methods showed promising technical performance in finish-line detection, crown design, digital segmentation, radiographic feature detection, and emerging image-based shade estimation. Shade-selection studies reported variable performance across machine-learning and image-based approaches, highlighting the influence of acquisition conditions and reference standards. Studies also evaluated static occlusal morphology and contact distribution, while evidence for dynamic occlusal function and AI-assisted design of multi-unit fixed dental prostheses remained limited. The evidence was heterogeneous and included predominantly in-vitro studies or limited clinical datasets. Sensor-enabled prostheses and robotic workflows remain emerging or experimental. AI may improve efficiency and consistency in selected workflows; however, current evidence does not support broad claims of autonomous clinical performance or consistent superiority over experienced clinicians and dental technicians. Multicentre external validation, standardised outcome measures, transparent reporting, and clinician oversight are required before routine implementation.

1. INTRODUCTION

Fixed prosthodontics has progressively moved from conventional analogue procedures toward digitally assisted design and manufacturing (Joda et al., 2017; Miyazaki et al., 2009). The integration of intraoral scanners, computer-aided design and computer-aided manufacturing (CAD/CAM), and three-dimensional (3D) printing has improved the reproducibility and precision of several restorative procedures (Joda et al., 2017). Earlier reviews documented the development and technical evolution of dental CAD/CAM systems (Miyazaki et al., 2009). Artificial intelligence (AI) encompasses computational approaches to pattern recognition, data interpretation, and decision support (Ding et al., 2023; Khanagar et al., 2021). An earlier systematic review of tooth-supported fixed and removable prosthodontics identified AI applications in shade selection, automated restoration design, preparation-finish-line mapping, and removable prosthesis design, while noting the need for further clinical evaluation (Revilla-León et al., 2023). Shade selection is particularly relevant to aesthetic fixed restorations, and

recent studies have explored machine-learning and image-based methods for standardising tooth colour and recommending restorative shades (Li et al., 2025; Ruan et al., 2026; Tao et al., 2026). In dentistry, machine learning (ML) and deep learning (DL) have been investigated across multiple specialties (Aljulayfi et al., 2024; Ding et al., 2023; Khanagar et al., 2021), including endodontics, dental radiology, and orthodontics (Ali et al., 2025; Asgary, 2024; Liu et al., 2023). Within restorative workflows, tasks such as finish-line delineation, occlusal modelling, and verification of digitally generated designs remain dependent on operator judgement and on the quality of acquired digital data and software-specific processing (Joda et al., 2017). Recent research has increasingly examined AI-assisted dental crown design (Broll et al., 2024; Kong and Kim, 2025). A recent bibliometric analysis examined the development of AI research in fixed prosthodontics, identifying major research themes and areas where clinical implementation remains limited (Li et al., 2026). Proof-of-concept models and a scoping review have reported promising technical performance, while also highlighting the predominantly in-vitro evidence base and the need for clinical validation (Farook et al., 2023; Kong and Kim, 2025; Yang et al., 2025). Against this background, this narrative review addresses the following question: how has AI been applied in fixed prosthodontics, what performance outcomes have been reported, and what limitations affect its clinical translation?

2. METHODS

To address this research question, an electronic PubMed search was conducted to identify English-language full-text publications from 1 January 2010. To supplement the PubMed search, reference lists of relevant publications and recent reviews were screened for additional eligible literature, including publications not indexed in PubMed. The search strategy combined AI-related terms with fixed-prosthodontic and restorative terms, using Medical Subject Headings (MeSH) and title/abstract terms: ("Artificial Intelligence"[Mesh] OR "artificial intelligence"[tiab] OR "machine learning"[tiab] OR "deep learning"[tiab] OR "generative artificial intelligence"[tiab] OR "generative AI"[tiab]) AND ("Denture, Partial, Fixed"[Mesh] OR "fixed prosthodontics"[tiab] OR "Crowns"[Mesh] OR "dental crown"[tiab] OR "dental crowns"[tiab] OR "fixed dental prosthesis"[tiab] OR "fixed dental prostheses"[tiab] OR "fixed dental bridge"[tiab] OR "fixed dental bridges"[tiab] OR "tooth preparation"[tiab] OR "finish line"[tiab] OR "margin detection"[tiab] OR "Computer-Aided Design"[Mesh] OR CAD/CAM[tiab] OR "implant-supported crown"[tiab] OR "implant-supported crowns"[tiab] OR "occlusal analysis"[tiab] OR "dental robotics"[tiab] OR "robot-assisted dentistry"[tiab] OR "dental sensor"[tiab] OR "intraoral sensor"[tiab] OR "dental biosensor"[tiab] OR "dental shade"[tiab] OR "tooth shade"[tiab] OR "shade selection"[tiab] OR "shade matching"[tiab] OR "tooth color"[tiab] OR "tooth colour"[tiab] OR "color matching"[tiab] OR "colour matching"[tiab]). Studies were considered eligible when they (1) evaluated or described an AI-, ML-, or DL-based method relevant to fixed prosthodontics or an associated fixed-restoration workflow; (2) reported quantitative performance measures or clinically relevant outcomes, or provided a relevant synthesis or conceptual discussion of the field; and (3) were peer-reviewed, published in English, and available as full text. Studies focused exclusively on removable prosthodontics or implant surgery without a fixed-restoration component, non-dental applications, conference abstracts, and letters lacking a relevant synthesis or conceptual contribution were excluded. Peer-reviewed editorials were considered eligible only when they provided a directly relevant conceptual discussion. Publications predating 2010 were retained only when needed to provide historical or technical context and were not treated as part of the contemporary AI evidence base. Similarly, a small number of studies describing non-AI supporting technologies (such as automated non-learning-based crown design, robotic systems, and in-vivo force measurement) were included only to provide technical context. Because the included studies differed substantially in algorithms, datasets, comparators, and outcome measures, their findings were synthesised narratively; no pooled quantitative analysis was performed. The review was prepared with reference to the six items of the Scale for the Assessment of Narrative Review Articles (SANRA)—justification of importance, aims, literature search, referencing, scientific reasoning, and presentation of relevant data—as a quality-improvement framework rather than as a systematic-review protocol or study-level risk-of-bias instrument (Baethge et al., 2019).

3. RESULTS

3.1 Overview of the Results

The literature was organised into seven application domains: (1) dental shade selection; (2) finish-line detection and margin delineation; (3) crown design, including occlusal morphology and contact analysis; (4) diagnostic and predictive modelling; (5) bio-intelligent and adaptive prostheses; (6) robotics and automated prosthodontic workflows; and (7) other supporting applications in material science and patient communication. Across these domains, AI applications included automated identification and extraction of preparation margins, generation of crown designs, analysis of static occlusal morphology and

contact distribution, interpretation of diagnostic images, prediction of selected material or restoration-related outcomes, and early work on sensor-enabled and robotic systems. Table 1 summarises 58 selected publications directly relevant to fixed prosthodontics or to defined fixed-restoration workflows. The level of evidence varied considerably.

Table 1. Selected AI applications and related technologies in fixed prosthodontics: study characteristics and main findings

Study	Application	AI approach / study design	Main finding
Overviews and evidence maps			
Aljulayfi et al., 2024	AI in prosthodontics	Systematic review; 30 studies	AI applications included restoration detection, shade selection, crown design and finish-line identification.
Revilla-León et al., 2023	AI in fixed and removable prosthodontics	Systematic review; 36 studies	Applications included shade selection, restoration design and finish-line mapping; clinical validation remained limited.
Boca et al., 2026	AI in prosthodontics	Scoping review; 50 studies	The review identified multiple prosthodontic AI applications but highlighted limited evidence of clinical utility.
Khaohoen et al., 2026	Treatment planning and outcome prediction	Scoping review; 20 studies	Applications included implant planning, crown design, full-arch optimisation and outcome prediction.
Li et al., 2026	Research trends in fixed prosthodontics	Bibliometric analysis; 377 publications	Deep learning, digital dentistry and 3D printing were the main research themes.
Dental shade selection			
Li et al., 2025	Tooth-colour standardisation and shade recommendation	Two-stage machine-learning colour correction; in-vitro photograph-based study	Colour difference decreased from 7.6 to 1.0; shade-recommendation accuracy was 73.1%.
Ruan et al., 2026	Personalised shade recommendation	Grey relational analysis plus DNN; 150 participants	Shade-selection accuracy was 93.2%, compared with 68.5% for visual and 82.7% for spectrophotometric assessment.
Tao et al., 2026	Image-based dental shade matching	PerceptShade; 1,553 images from 357 patients plus 50 independent cases	Top-1 and Top-3 accuracy reached 79.12% and 96.44%, respectively; independent-case agreement was 76.0%.
Şahin et al., 2025	AI-assisted tooth-colour matching	In-vitro comparison; 13 acrylic teeth; ChatGPT-4, Gemini 1.5 Pro and Easyshade	Mean ΔE00 was 2.84 with ChatGPT-4, 1.94 with Gemini and 0.70 with Easyshade.
Ünal and Polatoğlu, 2026	Clinical shade-selection agreement	Clinical study; 85 participants; traditional, spectrophotometric, IOS and ChatGPT-4 methods	Agreement among the four methods was slight (Fleiss κ = 0.071); traditional–ChatGPT-4 agreement was low and not significant.

Study	Application	AI approach / study design	Main finding
Shetty et al., 2024	AI-based dental shade matching	Systematic review; 15 studies	Shade-prediction performance varied with lighting, measuring devices and colour-space models.
Awdaljan et al., 2024	AI-assisted ceramic colour reproduction	Clinical technique report; Matisse AI software	The report described AI-assisted shade assessment and ceramic and staining recipes for an implant-supported central incisor.
Finish-line detection and margin delineation			
Alsheghri et al., 2024	Finish-line generation	AdaPoinTr; 1,047 3D scans	Median Chamfer and Hausdorff distances were 0.137 and 0.242 mm, respectively.
Alsheghri et al., 2025	3D margin-line extraction	Deep-learning segmentation; 1,113 scans	The Dice coefficient was 0.986, compared with 0.974 for graph-cut segmentation.
Choi et al., 2024	Finish-line detection	Dentbird versus 3Shape, exocad and MEDIT; 182 scans	Dentbird performed better for posterior concave finish lines, particularly in intraoral scans.
Sawangsri et al., 2025	Finish-line and crown-contour design	Two AI-equipped computer-aided design (AI-CAD) systems versus technicians; 100 abutments	Automate showed lower finish-line and contour deviations; Dentbird had lower acceptability.
Crown design: model development and reconstruction			
Farook et al., 2023	Partial-crown design	3D-CNN; in-vitro proof-of-concept; 30 selected pairs split 2:1	Maximum validation accuracy for partial-crown design was 60%.
Hosseinimanesh et al., 2025	Crown-mesh generation	Transformer-based deep learning	Chamfer distance decreased by 12.3% and mean squared error by 46.4% versus the previous model.
Yang et al., 2025	Full-crown design	DCrownFormer+ deep-learning model	Generated crowns showed improved shape completeness and surface smoothness.
Broll et al., 2024	Generative restoration design	Narrative review	The review identified generative deep learning as a potential approach for partial- and full-tooth reconstruction.
Binvignat et al., 2025	Central-incisor reconstruction	DeepSDF versus principal component analysis	DeepSDF produced more accurate anatomical reconstructions than principal component analysis.
Chau et al., 2024	Single-molar crown generation	GAN-based feasibility study	AI-generated molar crowns were feasible, but geometric overlap and accuracy remained limited.
Chen et al., 2024	Anterior tooth reconstruction	ToothDIT deep-learning model; 90 incisor models	ToothDIT reconstructed personalised anterior-tooth morphology with satisfactory accuracy.
Roh et al., 2024	Occlusal depth-image generation	Two-stage segmentation and GAN inpainting	MSE decreased from 0.007001 to 0.002618, while Dice increased from 0.9333 to 0.9648.
Broll et al., 2025	Crown design input data	Retrospective in-vitro study; 30 patients	Quadrant and full-arch scans performed similarly; adjacent-tooth-only inputs increased errors and failures.

Study	Application	AI approach / study design	Main finding
Crown design: comparative studies			
Cho et al., 2023	GAN-based crown design	Comparative study; 30 prepared posterior-tooth scan datasets	GAN-assisted design reduced working time and improved occlusal morphology and internal fit.
Chen et al., 2022	Lithium-disilicate crown morphology	AI versus technician and student designs; 12 participants	AI designs showed the greatest occlusal-profile discrepancy, although fracture loads were similar.
Nagata et al., 2025	Crown-design accuracy and time	AI-equipped CAD versus conventional CAD; five technicians	Mean between-technician differences were 25.7 ± 13.0 μm with AI-CAD and 275.5 ± 116.8 μm with conventional CAD.
Wu et al., 2025	AI-CAD software comparison	In-vitro comparison of Automate, Dentbird and conventional CAD	AI reduced design time, but accuracy varied between software systems and surfaces.
Wang et al., 2025	Full-crown morphology	AI versus technician-designed crowns	Overall morphology was comparable, but functional cusp-wear facets were not consistently reproduced.
Hlaing et al., 2026	Anterior and posterior crown design	Typodont comparison of deep-learning and conventional CAD	Deep-learning designs showed greater surface deviation but higher FDI clinical-quality scores.
Liu et al., 2024	Crown-design accuracy and efficiency	AI, digital CAD and wax-up comparison	Surface deviation was 68.4 μm with AI and 51.0 μm with digital CAD; AI reduced design time.
Liu et al., 2025	Zirconia crown design and occlusal contacts	AI versus digital design; 20 in-vitro replicas plus six clinical crowns (3 patients)	AI crowns showed lower surface deviations but 1.8-fold greater occlusal space.
Çakmak et al., 2024	Anterior crown design	Deep learning versus technician CAD; 25 scan datasets	Technician refinement reduced incisal-path deviation from 290.4 to 132.0 μm.
Xie et al., 2025	Crown morphology	AI versus manual CAD; 30 restorations	Median global deviation did not differ significantly between AI and manual CAD (79.8 vs 68.6 μm; $p = 0.1056$).
Cho et al., 2026	Anterior crown design	Dentbird and Automate versus technician; 25 designs	AI systems achieved comparable results for selected design criteria, with differences depending on the parameter assessed.
Crown design: evidence syntheses			
Kong and Kim, 2025	AI crown-design accuracy	Scoping review; 10 in-vitro studies	AI reduced design time in several studies; no in-vivo validation was reported.
Holiel et al., 2026	AI crown-design accuracy and function	Systematic review and meta-analysis; 17 studies (13 pooled)	AI reduced design time by 25–50%, with comparable pooled morphological accuracy.

Study	Application	AI approach / study design	Main finding
Hu et al., 2026	AI versus conventional CAD crown design	Meta-analysis; 12 in-vitro studies	AI shortened design time and improved pooled occlusal accuracy; differences in occlusal morphology were not significant.
Limpuangthip et al., 2026	Fixed-restoration design	Systematic review; 15 studies	AI reduced design time, while human refinement remained necessary for contacts, occlusion and aesthetics.
Revilla-León et al., 2026b	Automated restoration design	Systematic review; 24 studies	AI reduced restoration-design time, but accuracy varied by restoration type and study methods.
Multi-unit, implant-supported and clinical applications			
Sawangsri et al., 2026	Three-unit fixed dental prostheses	Dentbird and Atomica AI versus technicians; 30 three-unit fixed dental prostheses (FDPs)	Dentbird generated all designs (100%), whereas Atomica AI achieved a 93% overall success rate (83% for anterior and 100% for posterior FDPs).
Cho et al., 2024	Posterior implant-supported crowns	Laboratory comparison; 20 casts	Deep learning reduced design time, but occlusal-contact number and intensity differed between workflows.
Win et al., 2025	Complete-crown fit	Clinical comparison; 62 patients	Buccal, mesial and distal fit was similar; AI crowns showed greater lingual and occlusal discrepancies.
Lerner et al., 2020	Implant-supported zirconia crowns	Retrospective clinical study; 106 crowns	Three-year survival was 99.0%, and success was 91.3%.
Marques et al., 2026	Immediate implant interim crown	Clinical report	AI-assisted segmentation was used for immediate implant planning and interim crown design.
Gonzalez et al., 2026	Anterior implant emergence profile	Clinical technique report	AI tooth segmentation and CAD mirroring were used to design the anterior implant emergence profile.
Occlusal registration			
Ntovas et al., 2026	AI-assisted occlusal registration	Clinical comparative study; 46 participants	AI registration identified more true-positive and fewer false-positive occlusal contacts.
Revilla-León et al., 2026a	AI functions in intraoral scanners	Systematic review; seven studies	Occlusal-collision correction improved intercuspal accuracy in three of four studies.
Diagnostic and predictive modelling			
Tanveer et al., 2024	Marginal bone-loss detection	Systematic review; five studies	CNN performance was comparable to or better than human examiners for marginal bone-loss detection.
Yurttas et al., 2024	Fixed-prosthesis detection	YOLO-v5x; 8,000 panoramic radiographs	Restoration detection achieved precision and sensitivity values of 0.98–0.99.

Study	Application	AI approach / study design	Main finding
Fasih et al., 2025	Implant-prosthesis vertical misfit	ResNet-50 and U-Net; 638 radiographs	ResNet-50 achieved 92.7% accuracy; U-Net achieved 98% segmentation accuracy.
Elgarba et al., 2025	Intraoral scanner–cone-beam computed tomography (IOS–CBCT) registration	AI crown segmentation; 30 scan pairs	Crown segmentation achieved a Dice coefficient of 0.91; clinically acceptable IOS–CBCT registration reached 91%.
Xu et al., 2025	Tooth/crown segmentation	Systematic review and meta-analysis	Pooled mean IoU for tooth/crown segmentation was 90.15%; deep learning reduced segmentation time.
Tuntiwong et al., 2024	Zirconia-crack detection	Deep learning and acoustic-emission signals	Zirconia-crack localisation achieved 99.47% accuracy under laboratory conditions.
Yamaguchi et al., 2019	Crown-debonding prediction	CNN; 24 clinical cases (8,640 images)	Image-level accuracy for crown-debonding detection was 98.5%, with an AUC of 0.998.
Chang et al., 2024	Vertical root-fracture prediction	Deep-learning model; retrospective dataset of 145 teeth	Vertical root-fracture prediction achieved 80.7% accuracy.
Materials science			
Li et al., 2022	Resin-composite materials	Machine-learning regression; 12 commercial products (dataset augmented to 120 records)	Filler content and TEGDMA were the main predictors of flexural strength; UDMA was present in all high-predicted-strength compositions.

Abbreviations: 3D, three-dimensional; AI, artificial intelligence; AI-CAD, AI-equipped computer-aided design; AUC, area under the curve; CAD, computer-aided design; CBCT, cone-beam computed tomography; CNN, convolutional neural network; DeepSDF, deep signed distance function; DNN, deep neural network; FDI, FDI World Dental Federation; FDPs, fixed dental prostheses; GAN, generative adversarial network; IoU, intersection over union; IOS, intraoral scanner; MSE, mean squared error; TEGDMA, triethylene glycol dimethacrylate; UDMA, urethane dimethacrylate; YOLO, You Only Look Once; ΔE00, CIEDE2000 colour difference; $\varkappa$, Fleiss kappa coefficient.

3.2 AI-Assisted Dental Shade Selection

AI-based shade-selection research has focused on photographic colour correction and restorative-shade recommendation. Across three recent studies, reported performance was promising but varied by method and reference standard: two-stage machine-learning colour correction reduced the reported colour difference from 7.6 to 1.0, and shade-recommendation accuracy was 73.1%; a personalised recommendation model achieved 93.2% accuracy; and the PerceptShade framework reported top-1 and top-3 accuracies of 79.12% and 96.44%, respectively, with 76.0% top-1 agreement in the 50 independent cases used for the observer study (Li et al., 2025; Ruan et al., 2026; Tao et al., 2026). These results suggest a potential role for AI in supporting shade communication and candidate selection. However, differences in image acquisition, lighting, datasets, and reference methods prevent direct comparison, and the evidence does not support replacing spectrophotometric assessment or professional judgement.

Additional evidence illustrates the limitations of image-based shade estimation. Şahin et al. (2025) compared ChatGPT-4 and Gemini 1.5 Pro with an Easyshade spectrophotometer using 13 acrylic teeth; mean colour differences (ΔE00) were 2.84, 1.94 and 0.70, respectively, with the spectrophotometer performing significantly better than either AI application. In a clinical study

of 85 participants, Ünal and Polatoğlu (2026) found only slight overall agreement among traditional, spectrophotometric, intraoral-scanner and experimental ChatGPT-4 shade selection (Fleiss $\varkappa = 0.071$); agreement between traditional selection and ChatGPT-4 was low and not statistically significant. These findings caution against treating general-purpose image-recognition chatbots as reliable standalone shade-selection tools. A systematic review of 15 studies likewise identified lighting, measuring devices and colour-space models as important sources of variation (Shetty et al., 2024). Awdaljan et al. (2024) described the use of Matisse AI software to generate ceramic and staining recipes for a single implant-supported central-incisor restoration. The available evidence suggests that AI may support dental shade selection through photographic colour correction, shade recommendation, and digital communication of restorative colour information. However, its performance remains dependent on image acquisition conditions, reference standards, and the specific method used.

3.3 Finish-Line Detection and Margin Evaluation

AI-based methods for automated identification and extraction of preparation margins are among the more extensively investigated applications in fixed prosthodontics (Aljulayfi et al., 2024; Kong and Kim, 2025). Accurate delineation of the finish line is important for defining the design boundary of a restoration and supporting appropriate marginal fit and contour (Alsheghri et al., 2025; Choi et al., 2024).

Studies of AI-assisted finish-line delineation report good technical agreement with expert annotations or conventional segmentation methods. AdaPoinTr achieved median Chamfer and Hausdorff distances of 0.137 and 0.242 mm, respectively, while a separate deep-learning method achieved a Dice coefficient of 0.986 compared with 0.974 for graph-cut segmentation (Alsheghri et al., 2024, 2025). Comparative evaluations of commercial systems found performance differences according to scan type, finish-line geometry, and software. Dentbird demonstrated better finish-line extraction for posterior teeth with concave regions than 3Shape, exocad, and MEDIT, particularly for intraoral scans (Choi et al., 2024); by contrast, another comparison found lower deviations with Automate and lower acceptability scores for Dentbird than for Automate and dental technicians (Sawangsri et al., 2025).

Overall, automated margin detection is one of the more developed AI applications in fixed prosthodontics, but its performance remains dependent on scan quality, preparation geometry, soft-tissue interference, and software. AI-generated margins therefore require professional review before being used for definitive restoration design.

3.4 Crown Design and Occlusal Contact Analysis

AI algorithms, particularly deep-learning approaches, are increasingly being applied to the design of fixed restorations, especially single crowns (Broll et al., 2024; Kong and Kim, 2025). Depending on the system, crown geometry may be generated or completed from intraoral or laboratory scans, with the aim of reducing manual design time while maintaining anatomical, marginal, and functional requirements (Hosseinimanesh et al., 2025; Yang et al., 2025).

AI-assisted crown generation has been investigated through deep-learning models for partial- and full-crown reconstruction. Reported outcomes include improved mesh-completion metrics and anatomical reconstruction, although early proof-of-concept work also showed modest validation performance (Binvignat et al., 2025; Farook et al., 2023; Yang et al., 2025). Compared with its earlier Dental Mesh Completion model, the transformer-based network developed by Hosseinimanesh et al. reduced Chamfer distance by 12.3% and mean squared error by 46.4% (Hosseinimanesh et al., 2025). Generative approaches have also reduced design time and, in selected comparisons, improved occlusal morphology or internal fit (Broll et al., 2024; Cho et al., 2023). A non-learning automated crown-design workflow was also included as technical context (Jin et al., 2023).

Head-to-head comparisons indicate that AI can shorten crown-design time, but geometric accuracy and clinical acceptability vary across systems, surfaces, and restorative scenarios. Some studies reported favourable deviations or consistency, whereas others found larger surface or occlusal discrepancies (Chen et al., 2022; Hlaing et al., 2026; Liu et al., 2024, 2025; Nagata et al., 2025; Wang et al., 2025; Wu et al., 2025). In one anterior-crown study, technician refinement reduced incisal-path deviation (Çakmak et al., 2024). Nagata et al. reported mean between-technician differences in occlusal-surface misfit of 25.7 ± 13.0 μm with AI-equipped CAD versus 275.5 ± 116.8 μm with conventional CAD among five technicians; because no external reference was used, these values indicate greater design consistency rather than accuracy against a reference design (Nagata et al., 2025). Thus, design speed alone is insufficient to establish restorative accuracy.

Additional comparative and reconstruction studies support this mixed interpretation. Xie et al. (2025) found no significant difference in median global surface deviation between AI and manual designs (79.8 versus 68.6 μm; p = 0.1056), although maximum deviations were greater with AI. Broll et al. (2025) reported similar reconstruction performance using quadrant and full-arch scans, but reduced accuracy when only adjacent-tooth data were available. Earlier model-development studies explored single-molar generation, personalised anterior-tooth templates, and two-stage occlusal depth-image generation (Chau et al., 2024; Chen et al., 2024; Roh et al., 2024). A comparative anterior-crown study also found parameter-dependent differences between automated and technician workflows (Cho et al., 2026).

Recent evidence syntheses provide a broader quantitative perspective. Hu et al. (2026), in a meta-analysis of 12 in-vitro studies, found that AI shortened crown-design time and improved pooled occlusal accuracy compared with conventional CAD, whereas the pooled difference in occlusal morphology discrepancy was not significant; AI-generated cusp angles also remained smaller and required further optimisation. Holiel et al. (2026) included 17 studies, with 13 contributing to meta-analysis, and reported comparable morphological accuracy and internal fit alongside improved workflow efficiency. Two further systematic reviews reported consistent findings: Limpuangthip et al. (2026) synthesised 15 comparative studies and reported improved design-time efficiency, while emphasising the need for human refinement of proximal contacts, occlusion and aesthetics, and Revilla-León et al. (2026b) reviewed 24 studies of automated restoration and occlusal-device design, finding shorter design times but heterogeneous accuracy outcomes. However, these studies emphasised that the evidence was predominantly laboratory-based and that prospective clinical validation remains insufficient.

Evidence on occlusal contacts and broader restorative workflows is still limited. AI-based intraoral-scanner registration has improved the identification of static contacts in selected studies, but contact number, intensity, and occlusal space have not been consistently reproduced (Cho et al., 2024; Liu et al., 2025; Ntovas et al., 2026; Revilla-León et al., 2026a). For three-unit fixed dental prostheses (FDPs), automated systems achieved high design-completion rates but scored less favourably than technicians for some contact and connector parameters in an in-vitro comparison (Sawangsri et al., 2026). Clinical evidence remains still limited (Gonzalez et al., 2026; Lerner et al., 2020; Marques et al., 2026; Win et al., 2025).

3.5 Diagnostic and Predictive Modelling

AI applications in diagnosis and prediction cover radiographic identification of restorations, detection of prosthetic misfit or marginal bone loss, digital segmentation, material-damage classification, and estimation of restoration-related complications. Across these distinct tasks, studies have reported promising image- and laboratory-based performance, including high detection metrics for fixed restorations, 92.7% accuracy for implant-prosthesis misfit classification, a Dice coefficient of 0.91 for crown segmentation used in intraoral scanner–cone-beam computed tomography (IOS–CBCT) registration, and a pooled mean intersection over union (IoU) of 90.15% for tooth/crown segmentation (Elgarba et al., 2025; Fasih et al., 2025; Tanveer et al., 2024; Xu et al., 2025; Yurttas et al., 2024). Crack classification has also shown high accuracy under experimental loading, but this does not establish clinical diagnostic utility (Tuntiwong et al., 2024).

Predictive applications require particular caution. A crown-debonding model reported 98.5% image-level accuracy but was derived from only 24 clinical cases, while a model for vertical root-fracture prediction achieved 80.7% accuracy in a retrospective dataset of 145 teeth (Chang et al., 2024; Yamaguchi et al., 2019). These findings are exploratory and should not be equated with validated patient-level prediction. More broadly, the tasks and performance metrics are not directly comparable; independent external validation and prospective evaluation using clinically meaningful outcomes remain necessary.

3.6 Bio-Intelligent and Adaptive Prostheses

Bio-intelligent or sensor-enabled prostheses are currently a developmental concept rather than an established clinical application. Proposed systems could monitor occlusal loading, temperature, or wear, drawing on earlier in-vivo force-measurement technologies; however, these technologies have not yet been integrated into validated AI-enabled fixed restorations (Assoratgoon et al., 2022; Kawaguchi et al., 2007; Rana et al., 2025). Sensor integration, durability, calibration, power supply, data transmission, and biocompatibility remain unresolved, and evidence that continuous monitoring improves patient outcomes is lacking.

3.7 Robotics and Automated Prosthodontic Workflows

Robotics may eventually support the physical execution of digitally planned procedures, including tooth preparation and prosthesis handling. Current prosthodontic literature is largely exploratory, and some reviewed applications, such as robotic denture-tooth arrangement, relate to removable rather than fixed prosthodontics. Evidence for routine robotic workflows in fixed restorations remains limited, with safety, tactile feedback, adaptability, cost, and professional responsibility requiring further evaluation (Alqutaibi et al., 2025; Karnik et al., 2024).

3.8 Other Supporting Applications: Materials Science and Patient Communication

Two adjacent applications concern material-property modelling and patient communication rather than direct fixed-restoration outcomes. Machine-learning analysis of CAD/CAM resin-composite blocks identified material-composition features associated with predicted flexural strength, but the original dataset contained only 12 products (Li et al., 2022). A comparison of three chatbots answering prosthesis-related questions found differences in response quality and readability, with Gemini receiving the highest mean quality score (Esmailpour et al., 2025). These applications may support research and patient education, but neither demonstrates improved clinical outcomes; AI-generated patient information requires professional review.

4. DISCUSSION

The evidence suggests that AI is most mature in fixed-prosthodontic tasks with clearly defined digital inputs and measurable outputs, particularly finish-line delineation, crown-shape generation, and digital segmentation. These tasks can be evaluated against expert annotations or digital reference surfaces, allowing technical performance to be quantified and compared more directly than many biological or patient-dependent outcomes (Boca et al., 2026; Kong and Kim, 2025; Xu et al., 2025). AI-assisted shade selection is an important but less standardised application. Recent studies have examined photographic colour correction, patient-specific shade recommendation, and image-based matching under variable lighting; however, the methods, reference standards, and reported performance differ (Li et al., 2025; Ruan et al., 2026; Tao et al., 2026). Evidence for multi-unit restorations is less developed than that for single crowns, while occlusal registration and dynamic function remain distinct challenges (Khaohoen et al., 2026; Ntovas et al., 2026; Sawangsri et al., 2026).

The shade-selection evidence also reinforces the need to distinguish experimental feasibility from clinical reliability. In particular, the lower colour differences achieved by spectrophotometry than by ChatGPT-4 or Gemini in a controlled in-vitro comparison, together with the weak agreement observed in a clinical comparison, indicate that general-purpose AI image tools should not replace validated instrumental shade assessment (Şahin et al., 2025; Ünal and Polatoğlu, 2026). In crown design, recent meta-analyses suggest a consistent time-saving advantage, but do not establish uniform superiority in morphology or functional outcomes; technician refinement remains important (Holiel et al., 2026; Hu et al., 2026).

The evidence base is heterogeneous and should not be interpreted as demonstrating equivalent levels of clinical readiness across applications. Many studies rely on in-vitro specimens, small or selected datasets, software-specific workflows, and internal validation, limiting generalisability to different scanners, cameras, operators, and clinical settings (Farook et al., 2023; Kong and Kim, 2025; Yamaguchi et al., 2019). Outcomes also vary substantially: surface deviation, trueness, margin-detection agreement, design-completion rates, and image-classification accuracy measure different aspects of performance and cannot be compared directly. Recent evidence syntheses similarly report methodological weaknesses, inconsistent outcome reporting, and a gap between promising technical results and demonstrated patient-centred benefit (Alfaraj et al., 2026; Boca et al., 2026; Li et al., 2026). For shade selection, imaging conditions, colour spaces, reference methods, and algorithm choice may influence results; the available studies therefore do not yet establish a consistent advantage of AI over established visual or instrumental approaches (Li et al., 2025; Ruan et al., 2026; Tao et al., 2026).

Clinical evidence is emerging but remains limited. Comparative clinical data suggest that AI-assisted crown workflows can achieve acceptable fit in selected regions, although discrepancies have also been reported; retrospective survival data without an appropriate control group cannot establish that AI itself improves restoration outcomes (Lerner et al., 2020; Win et al., 2025). The diagnostic and predictive literature requires similar caution. Detecting the presence of a restoration, identifying a radiographic misfit, classifying an image, and predicting a future complication are different tasks with different clinical implications. Prediction models, in particular, require patient-level external validation and prospective assessment before they can support reliable risk estimates or treatment decisions (Chang et al., 2024; Fasih et al., 2025; Yamaguchi et al., 2019; Yurttas

et al., 2024). Current reviews of AI in dentistry and prosthodontics reinforce that much of the evidence remains at the technical-validation stage, and that the number of clinical studies with meaningful follow-up is still limited (Aljulayfi et al., 2024; Boca et al., 2026; Khanagar et al., 2021; Khaohoen et al., 2026).

AI-supported occlusal analysis also requires careful interpretation. Digital contact distribution is only one component of occlusal function and does not reproduce mandibular movements, neuromuscular adaptation, or patient-specific functional patterns. Future studies should combine digital contact analysis with validated clinical assessment and, where appropriate, dynamic motion data. Bio-intelligent prostheses and AI-robotic workflows are promising research directions, but current evidence remains largely conceptual, experimental, or adjacent to fixed prosthodontics. Although force-sensing methods provide a technical foundation for future monitoring, durable and biocompatible integration into routine restorations has not been established (Alqutaibi et al., 2025; Assoratgoon et al., 2022; Karnik et al., 2024; Kawaguchi et al., 2007; Rana et al., 2025).

This review has several limitations. The electronic search was restricted to PubMed and to English-language full-text publications, supplemented by reference-list screening; relevant studies indexed only in other databases or published in other languages may therefore have been missed.

Future research should prioritise prospective multicentre datasets, independent external validation, standardised image-acquisition and reference protocols, harmonised clinically meaningful endpoints, and transparent reporting of model development and testing. Evaluation should extend beyond technical accuracy to include workflow impact, restoration complications and survival, occlusal adjustment, and patient-reported outcomes. In clinical practice, AI should be used as decision support under professional oversight; clinicians and dental technicians remain responsible for verifying shade, margins, fit, contacts, occlusion, and restoration suitability. Interoperability, data protection, biocompatibility, and post-deployment performance monitoring are also necessary (Boca et al., 2026; Khaohoen et al., 2026; Li et al., 2026).

5. CONCLUSIONS

AI has shown promising technical performance in selected fixed-prosthodontic workflows, including margin delineation, crown design, digital segmentation, and emerging shade-selection applications. However, performance remains task- and system-dependent, and much of the evidence is based on laboratory validation or limited clinical datasets. Current findings do not support autonomous use or consistent superiority over clinicians and dental technicians. Routine implementation will require prospective multicentre validation, standardised clinically meaningful outcomes, transparent reporting, appropriate data governance, and continued professional oversight.

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AUTHOR CONTRIBUTIONS

Andri Çabeli: Conceptualization, Investigation, Writing – original draft.

Neada Hysenaj: Conceptualization, Methodology, Supervision, Writing – review and editing.

Vergjini Mulo: Validation, Writing – review and editing.

Edit Xhajanka: Data curation, Validation, Supervision, Writing – review and editing.

All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors declare no competing interests.

ETHICS STATEMENT

Not applicable. This narrative literature review did not involve new research with human participants or animals. Consent for publication: not applicable; no identifiable individual-level data are presented.

DATA AVAILABILITY STATEMENT

Not applicable. No new datasets were generated for this narrative review; the information supporting the synthesis is available in the cited publications.

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