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AI-Assisted Occlusal Design and Adjustment in Prosthodontics: A Systematic Review of Fit Accuracy, Occlusal Trueness and Workflow Efficiency

Salah A. Yousief[1*], Nasser Hussein Shaheen[2], Dina Wafik Elkassas[3], Hala Aly Maher Ragab[4], Ahmed Heji Albaqawi[5] and Dalia A. Magdi[6]

[1]Department of Restorative and Prosthetic Dental Sciences, College of Dentistry, Dar Al Uloom University, Riyadh 13313, Saudi Arabia
[2]Restorative and Prosthetic Dental Sciences Department, Dar Al Uloom University, Riyadh 13313, Riyadh, Saudi Arabia
[3]Department of Restorative Dentistry, Faculty of Dentistry, Misr International University, Egypt
[3]Department of Clinical Dentistry, College of Dentistry, Princess Nourah Bint Abdulrahman University, Saudi Arabia
[4]Department of Clinical Dental Science, Princess Nourah Bint Abdulrahman University – College of Dentistry
[5]Department of Restorative Dental Science, College of Dentistry, University of Ha'il, Ha'il, Saudi Arabia
[6]Faculty of Computers and Information, Sadat Academy for Management Sciences, Cairo, Egypt

Author Designation: [2,3]Professor

*Corresponding author: Salah A. Yousief (e-mail: Salah.a@dau.edu.sa).

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Abstract **Objectives:** Artificial Intelligence (AI) based tools are increasingly used in prosthodontic design and occlusal analysis. They now appear at several steps of the digital workflow: crown design, registration of the occlusal relationship and correction of virtual occlusal contacts. It is not clear whether these tools give restorations that fit and occlude as well as those made with conventional workflows. This systematic review summarises the evidence on AI-assisted occlusal design and adjustment, with technical accuracy as the primary outcome. **Methods:** The review followed PRISMA 2020 and was not registered in advance. PubMed, Scopus and the Cochrane Library were searched for English-language articles published from 2015 to 2025. Eligible studies compared an AI-based tool for crown design, occlusal registration or occlusal contact correction with a conventional workflow. Two reviewers independently screened studies, extracted data and assessed risk of bias, using an adapted QUIN tool for laboratory studies and ROBINS-I for clinical studies. Results were synthesised narratively by intervention and outcome. **Results:** The search identified 150 records and 12 studies met the inclusion criteria: two comparative clinical studies (17%), one laboratory study with three supplementary clinical cases (8%) and nine laboratory studies (75%). No randomised trial was found. No study reported follow-up beyond the scanning or seating visit and none reported validated patient-reported outcomes. In a paired clinical study of 62 patients, AI-designed crowns were equivalent to conventionally designed crowns for most marginal and internal gap measures, but the lingual marginal gap and the occlusal discrepancy were larger with AI design (149±66 Vs 105±63 µm; mean difference 43.9 µm, 90% CI 38.6 to 49.4, outside the ±15 µm equivalence margin). In laboratory studies that measured it, AI crown design shortened design time. AI-based occlusal registration was less accurate than the scanner's own articulation in three of four studies of the same platform. AI-driven Occlusal Contact Adjustment (AI-OCA) improved the trueness of virtual occlusal records at some interarch distances and reduced it at others. Four studies came from one research group using one platform. Heterogeneity precluded meta-analysis. **Conclusion:** The available studies measure technical accuracy at the time of fabrication. They say little about long-term clinical performance or patient benefit. AI-assisted crown design matched conventional design on most fit measures but produced larger occlusal discrepancies and results for AI-based registration and contact correction were mixed and depended on scanner and edentulous span. These findings are preliminary and should be treated as hypotheses. Well-designed clinical trials with standardized outcomes and long follow-up are needed before routine adoption.

Key Words Artificial Intelligence, Occlusal Design, AI-Assisted Occlusal Adjustment, Crown Design, Digital Dentistry, Systematic Review

INTRODUCTION

Artificial Intelligence (AI) is transforming dental practice by automating tasks that traditionally require human expertise [1,2]. In prosthodontics, AI applications include automated prosthesis design, smile prediction and virtual occlusal analysis [3,4]. Machine-learning algorithms have been integrated into digital workflows (e.g. intraoral scanners, CAD/CAM software) to optimize tooth morphology and occlusal contacts [5].

These systems can generate restorations with high morphological accuracy, reducing design time and operator variability [6,7].

Despite these advances, the impact of AI on prosthesis longevity and patient outcomes (comfort, function) remains uncertain. Occlusal adjustment is critical for restoration success: poorly adjusted occlusion can lead to prosthetic fractures, periodontal strain, or patient discomfort. Modern intraoral scanner software offers AI-driven occlusal contact adjustment to resolve digital bite interferences automatically. Laboratory reports indicate that this can improve the trueness of virtual interocclusal records under some conditions and not under others [8]. Other laboratory work found that AI-based registration of the maximum intercuspal position was less accurate than the scanner's own articulation in some set-ups [9,10].

Two features of this literature shaped the scope of the review. First, "occlusal adjustment" is used for several different things. It can mean chairside grinding of a restoration in the mouth, but in the AI literature it more often means a step that happens earlier: the way a crown's occlusal surface is designed, how two scans are registered into one occlusal relationship, or how interpenetrating contacts are corrected on screen. Second, we found no study of AI-guided adjustment of a restoration after delivery. Limiting the review to post-delivery adjustment would therefore have left it empty. We chose instead to define the scope as AI-assisted occlusal design and adjustment within the digital prosthodontic workflow and to treat the absence of post-delivery studies as an evidence gap. Earlier reviews of AI in prosthodontics were mostly scoping or general reviews that described the technology broadly [11-13]. We did not identify a systematic review centred on occlusal outcomes.

To keep the terms apart, we use the definitions in Table 1 throughout. The three AI interventions are AI-Assisted Crown Design (AI-CD), AI-based occlusal registration (AI-OR) and AI-Assisted Occlusal Contact Adjustment (AI-OCA). They act at different stages and carry different clinical risks, so they are reported separately.

The review question was framed with the PICOS structure. The population was prosthodontic restorations and models, either patients receiving single crowns or partial-arch restorations or the laboratory models that represent them (P). The intervention was an AI-based tool for crown design, occlusal registration or occlusal contact correction (I). The comparator was a conventional digital workflow, such as technician-designed CAD, scanner articulation without AI, or an uncorrected scan (C). The primary outcomes were technical accuracy measures: marginal and internal gap, occlusal discrepancy or occlusal contact accuracy and trueness and precision of occlusal records. The secondary outcomes were design time, occlusal morphology, clinical outcomes (survival, complications, wear, chairside adjustment) and patient-reported outcomes (O). Both clinical and laboratory comparative studies were eligible (S).

This review aims to evaluate studies of AI-assisted occlusal design and adjustment in prosthodontics. We focus on technical accuracy as the primary outcome (fit accuracy, occlusal contact metrics), with efficiency (design time) and clinical or patient-reported outcomes (survival, comfort, chewing efficiency) as secondary outcomes where they were reported. We also assess heterogeneity, bias and practical implications for clinicians. By summarising primary evidence from the past decade, we describe what the current studies can and cannot tell clinicians about AI-assisted occlusal technologies.

METHODS

Protocol and Registration

This systematic review was reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [15]. The review protocol was not registered in PROSPERO, the Open Science Framework or any other repository and no protocol was published before the work began. We return to this in the Limitations.

Eligibility Criteria

Studies were selected with predefined criteria, summarised in Table 2. Both in vitro and clinical studies were included; case reports and reviews were excluded. Studies were eligible only if they compared an AI-based intervention with a conventional workflow or a reference standard and reported outcomes of fit, occlusion or patient function.

Table 1: Definitions of the AI Interventions and Measurement Terms used in this Review

Term	Definition used in this review
AI-assisted Crown Design (AI-CD)	A trained model (for example a deep-learning or generative adversarial network) proposes the crown, including its occlusal surface, from the scanned preparation and neighbouring teeth. It acts before fabrication
AI-based Occlusal Registration (AI-OR)	A trained model locates the maxillomandibular relationship or the Maximum Intercuspal Position (MIP) from separate scans, replacing or refining the scanner's own articulation. It acts before fabrication
AI-assisted Occlusal Contact Adjustment (AI-OCA)	Software correction of virtual occlusal collisions or contact points in a digital occlusal record, for example resolving interpenetrating surfaces. It is a digital step and does not involve grinding a restoration
Post-delivery occlusal adjustment	Chairside selective grinding or addition on a restoration in the mouth, guided by articulating paper or digital occlusal analysis. No included study evaluated an AI-guided version
Virtual Occlusal Record (VOR)	The digital registration of the relationship between the upper and lower arches
Trueness	Closeness of the mean of repeated measurements to a reference value, here the deviation in µm from a reference scan or position (ISO 5725-1) [14]
Precision	Closeness of agreement between repeated measurements made under the same conditions [14]
Accuracy	The overall closeness of a result to the reference, combining trueness and precision. We use it only as an umbrella term and name the specific measure wherever possible [14]
Fit accuracy	The marginal and internal gap between a crown and its prepared abutment, in µm. A smaller gap means a better fit
Occlusal discrepancy	The deviation, in µm, of the occlusal surface or contact from the reference as each study defined it. The definitions were not identical across studies, so values are compared only within a study.

Table 2: Eligibility Criteria

Domain	Inclusion	Exclusion
Population or model	Natural-tooth or implant-supported fixed restorations (single crowns, partial-arch situations) in patients, or laboratory models representing them (typodonts, stone or resin casts, digital casts, abutment models)	Removable prostheses; non-prosthodontic applications
AI intervention	AI-based tools (machine learning, deep learning, generative models) used for crown design, occlusal registration or occlusal contact correction; AI-guided post-delivery adjustment would also have been eligible	AI used only for diagnosis, treatment planning or prediction; tools not described as AI-based
Comparator	Conventional CAD by a technician or clinician; scanner articulation without AI; uncorrected scan; or a stated reference standard	No comparator or reference standard
Outcomes	Primary: marginal and internal gap, occlusal discrepancy or contact accuracy, trueness and precision of occlusal records. Secondary: design time, occlusal morphology, clinical outcomes, patient-reported outcomes	Studies reporting none of these outcomes
Study design	Comparative clinical studies (randomised or not) and comparative laboratory studies with quantitative outcomes	Case reports, narrative or systematic reviews, editorials and letters
Language and period	English; published 2015 to 2025	Other languages; other dates
Publication type	Peer-reviewed full-text original articles	Conference abstracts, preprints, dissertations

The review was restricted to English-language articles because the reviewers could not reliably assess full texts in other languages and translation resources were not available. This choice may have missed relevant studies and introduces a risk of language bias.

Information Sources and Search Strategy

PubMed, Scopus and the Cochrane Library were searched for articles published from 2015 through 2025, Publication date from 2015/01/01 to 2025/12/31; language English. Search terms included combinations of "artificial intelligence", "machine learning", "deep learning", "digital occlusion", "occlusal adjustment", "dental prosthesis", "crown design" and related MeSH terms. Grey literature, preprints, trial registries, conference proceedings and dissertations were not searched and the reference lists of the included studies were not screened systematically. These limits are discussed below.

Study Selection

Duplicate records were removed and titles/abstracts were screened for relevance. Two reviewers screened titles and abstracts independently and then assessed the full texts of potentially eligible articles against the predefined criteria. Disagreements were settled by discussion or, when needed, by a third reviewer. Agreement between the two reviewers was measured with Cohen's kappa and interpreted with the thresholds of Landis and Koch [16]: κ = [value] for title and abstract screening and κ = [value] for full-text assessment.

Data Extraction

Two reviewers extracted data independently using a standardised extraction sheet. The sheet recorded study design, the experimental unit and the number analysed (participants, casts, crowns, scans or operators), the model or population, the AI tool and its developer where named, the comparator, the outcomes and how they were measured, the main quantitative results and follow-up. Values that a study did not report are marked NR. Disagreements were resolved by discussion or by a third reviewer. Outcomes were split into primary and secondary as described in the Introduction.

Quality Assessment and Risk of Bias

Two reviewers independently assessed the risk of bias for all included studies. Given the heterogeneity of study designs, a single universal tool was not applied. Disagreements between reviewers were resolved by consensus or referral to a third reviewer.

Clinical studies (n = 2). We used ROBINS-I [17], which is designed for non-randomised studies of interventions and covers within-patient paired comparisons. It rates seven domains (confounding, selection of participants, classification of interventions, deviations from intended interventions, missing data, measurement of outcomes and selection of the reported result) as low, moderate, serious, critical or no information. The overall rating follows the most severe domain. An earlier version of this review used the Newcastle-Ottawa Scale, which was replaced because it is meant for non-randomised observational designs. Cochrane RoB 2 was not applicable because none of the included studies randomised participants or interventions. Had one done so, RoB 2 (including its crossover variant) would have been used.

Laboratory studies (n = 10, including the study with three supplementary clinical cases). We used the Quality Assessment Tool for In Vitro Studies (QUIN) [18]. Its 12 criteria cover aims and objectives, sample-size calculation, sampling technique, the comparison group, methodology, operator details, randomisation, outcome measurement, assessor details, blinding, statistical analysis and presentation of results. Because several of these criteria overlap in small experimental studies, we grouped them into six domains: randomisation, blinding of the outcome assessor, control group, sample adequacy, outcome reporting and control of confounding (operator, scanner and specimen standardisation). Each applicable domain was scored 2 (adequately reported and addressed), 1 (partly or unclear) or 0 (not reported or inadequate). Domains that did not apply to a design were excluded from the denominator. The overall score is the sum of the domain scores divided by twice the number of applicable domains, expressed as a percentage and was classified as low risk above 70%, moderate risk from 50-70% and high risk below 50%, which are the QUIN cut-offs. For sample adequacy, a score of 2 required either an a priori sample-size calculation or at least 20 independent experimental units per group, 1 meant 10 to 19 units or no information and 0 meant fewer than 10 units.

Synthesis Methods

We planned a meta-analysis only if at least three studies of the same intervention reported the same outcome with means and standard deviations. That condition was not met (see Results), so we synthesised the findings narratively, grouped by intervention (AI-CD, AI-OR, AI-OCA) and by outcome, following the SWiM guidance [19-26]. Because several studies used the same AI platform, we also grouped results by platform or developer. We recorded what each study treated as its sample size. Repeated scans of the same cast were treated as repeated measurements and not as independent specimens, because counting them as independent observations would overstate the sample size.

RESULTS

Study Selection

The searches identified 150 records. After removing 30 duplicates, we screened 120 records by title and abstract and excluded 85. Thirty-five full-text articles were assessed for eligibility and 23 were excluded (total 23). Twelve studies were included (Figure 1). The numbers reconcile at each step (150-30 = 120; 120-85 = 35; 35-23 = 12).

Characteristics of the Included Studies

Twelve studies were included (Table 3). Two were comparative clinical studies (Ntovas *et al.* [20] with 46 participants and Win *et al.* [27] with 62 patients), one was a laboratory study with three supplementary clinical cases [28] and nine were laboratory studies (Tian *et al.* [8] four studies by [22-26]). In percentage terms, 17% were clinical, 8% were mixed and 75% were laboratory studies. Win *et al.* [27] compared two designs in the same patients without random allocation. We did not find a randomised trial. By intervention, five studies evaluated AI-CD, four evaluated AI-OR and three evaluated AI-OCA, with or without AI registration. Comparators were conventional CAD/CAM designs or unadjusted digital bites. Outcomes included fit accuracy (marginal and internal gaps), occlusal contact metrics, trueness and precision of occlusal records and design/adjustment time. No study reported validated patient-reported outcomes. The two clinical studies assessed their outcomes at a single visit (scanning or seating) and follow-up was not reported for the three cases in Liu *et al.* [28]; no study followed patients over time.

Sample size needs care here because the experimental units were not the same kind of thing. Participants contributed to only two studies (46 and 62). In the laboratory studies the unit was a cast, a scan, a crown design or an operator and these are not interchangeable. In the Revilla-León studies, n refers to repeated scans or duplicates of the same casts, so these values describe repetitions of a measurement rather than independent specimens. In Nagata *et al.* [26] the number of operators was five. In Wu *et al.* [23], 325 cast pairs were used, but 300 were for training and only 25 for validation. Table 3 lists the unit and number for every study.

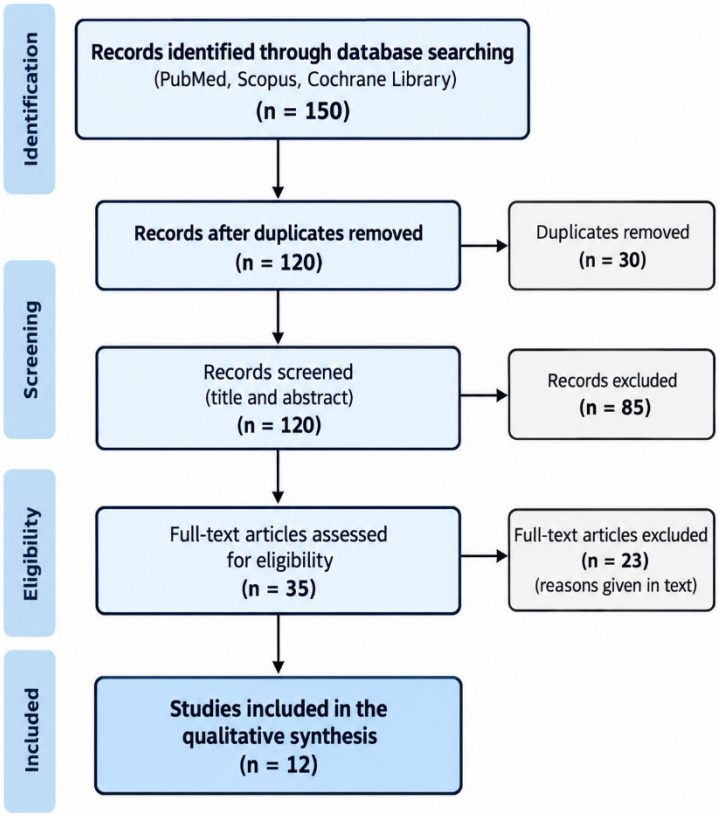

Figure 1: PRISMA 2020 Flow Diagram of Study Selection

Table 3: Summary of the Studies Included

Study	Study design	Unit of analysis and n	Population/setting	Intervention (AI tool/version)	Comparator	Outcomes measured	Key numerical results (as reported)	Follow-up
Tian *et al.* [8]	*In vitro* experimental	Scans or records; n NR	Typodont/implant restoration model; posterior edentulous segments; two scanners (TRIOS 4, TRIOS 5)	AI-OCA: AI-driven occlusal contact adjustment in scanner software (TRIOS 4/5 workflow)	No AI-OCA	Virtual occlusal record trueness across interarch distance bands	AI-OCA significantly affected VOR trueness (P<0.01): improved at D25–35 (both scanners), D26–36 and D27–37 (TRIOS 5), and reduced at D16–46 (both scanners); medians/IQR NR	Not applicable
Ntovas *et al.* [20]	Clinical comparative (within-participant scans; non-randomised)	46 participants	Participant scans at MIP	AI-OR plus AI-OCA: AI-based registration and occlusal collision correction (AI program; Bite-Finder referenced)	Standard IOS articulation ± non-AI post-processing (cast trimming/incisal pin adjustments)	True-positive/false-positive occlusal contacts Vs film	AI-registered groups had the highest true positives and fewer false positives vs non-postprocessed; means/SD NR	Single visit; no follow-up
Revilla-León *et al.* [21]	In vitro (cast repeat-scan)	15 repeated scans per subgroup	Conventional casts on articulator; 2 IOSs	AI-OR: AI-based program for maxillomandibular relationship (Bite-Finder) ± collision correction	IOS articulation with bilateral record; corrected vs non-corrected	Trueness/precision across 36 interlandmark distances	Significant trueness (P=.003) and precision (P<.001) differences; IOS-corrected and AI-articulated better than IOS non-corrected; numeric values NR	Not applicable
Revilla-León *et al.* [22]	In vitro (cast repeat-scan)	20 repeated scans (duplicates); subgroups n = 10	Casts; 4 IOS platforms	AI-OR plus AI-OCA: AI program (Bite-Finder) for MIP location; AI articulation and AI collision correction	IOS MIP articulation with bilateral record ± collision correction	MIP trueness/precision via 36 distances	Group/subgroup effects (P<.001). AI-articulated worse than IOS and IOS-corrected; AI improved iTero/Primescan but reduced TRIOS 4/i700; numeric values NR	Not applicable
Revilla-León et al. [9]	In vitro (stone casts)	20 duplicates; subgroups n = 10	Complete-arch vs half-arch scans; 3 IOSs	AI-OR: AI program (Bite-Finder) for MIP location/correction	IOS articulation workflows	MIP trueness/precision	Complete-arch better than half-arch; IOS outperformed AI overall; Primescan trueness > i700/Aoralscan 3; numeric values NR	Not applicable
Revilla-León *et al.* [10]	In vitro (edentulous-span casts)	n = 10 per subgroup	Casts with 0–4 posterior edentulous teeth	AI-OR: AI program (Bite-Finder) for MIP articulation	IOSs (Primescan, Aoralscan 3, i700)	MIP trueness/precision	Span and platform effects (P<.001): 0–2 edentulous teeth better than 4; Primescan/Aoralscan 3 > i700; IOS > AI overall; numeric values NR	Not applicable
Wu *et al.* [23]	Feasibility model study	325 stone cast pairs (300 training, 25 validation)	Stone cast pairs (≥12 occluding pairs)	AI-OR: deep-learning MIP prediction after ICP registration	ICP-derived reference alignment	Translational/rotational discrepancies	Rotation (mean±SD): x 1.407°±1.548; y 1.269°±8.476; z 0.730°±1.334. Translation: x 0.185±1.324 mm; y 1.222±0.848 mm; z −1.034±0.273 mm	Not applicable
Ding *et al.* [24]	In vitro + finite element	600 training and 12 test digital casts	Digital casts for crown design	AI-CD: 3D-DCGAN crown design	Biogeneric + natural-tooth reference	RMS, cusp angle, occlusal contacts, stress/fatigue	RMS (AI vs natural) 0.3611; cusp angle: biogeneric 67.11° > AI 49.43° and natural 54.05°; stress at 300 N: AI 26.73 MPa vs natural 23.97 MPa; occlusal contact number/area NS	Not applicable
Cho *et al.* [25]	In vitro comparative	20 casts	Implant-supported posterior crowns (resin casts)	AI-CD: deep learning-based automated crown design (DL as-generated; DL optimised)	Conventional CAD	Design time; occlusal morphology/contact endpoints	Design time (mean±SD): DL as-generated 82.9±30.4 s; DL optimised 321.7±98.3 s; conventional 370.3±98.3 s; DL as-generated fastest (P≤0.001)	Not applicable
Nagata *et al.* [26]	In vitro comparative	5 operators; 2 abutment models (#15, #26)	Abutment models #15/#26	AI-CD: AI CAD (Dentbird, Dentbird Solutions)	Conventional CAD (3Shape)	Trueness/precision; time; marginal fit	Trueness (μm): #15 conventional 275.5±116.8 vs AI 25.7±13.0; #26 230.5±66.8 vs 32.5±12.7. Design time (min): #15 397.2±80.4 vs 99.4±17.1; #26 516.4±61.3 vs 97.6±11.1	Not applicable
Win *et al.* [27]	Clinical comparative, paired (within-patient), non-randomised	62 patients; 124 crowns (62 per design)	Interim crowns seated intraorally	AI-CD: GAID: Dentbird Crown (V.3.X.X; Imagoworks)	CCAD: exocad DentalCAD 3.0 Galway	Marginal/internal gaps; occlusal contact discrepancy	Occlusal discrepancy: 149±66 μm (GAID) Vs 105±63 μm (CCAD); mean diff 43.9 μm (90% CI 38.6–49.4), not within ±15 μm equivalence margin; internal gaps within equivalence; lingual marginal gap larger with AI	Delivery visit only; no follow-up
Liu *et al.* [28]	Laboratory study with three supplementary clinical cases	*In vitro* 10 crowns per group; 3 clinical cases	Zirconia crown design + 3 cases	AI-CD: AI design (no technician adjustment)	Digital design (technician adjusted margins/occlusion/contacts)	RMS accuracy; proximal/occlusal contacts; marginal gaps	In vitro RMS (μm): AI 13±3 (STL), 18±2 (scan) vs digital 45±3 (STL), 120±15 (scan). Case I occlusal contact −283±36 vs −184.7±26.5; margin gap 332±32 vs 276±25 (P=.0001 overall)	NR

AI-CD, AI-assisted Crown Design; AI-OR, AI-based Occlusal Registration; AI-OCA, AI-assisted Occlusal Contact Adjustment (definitions in Table 1). IOS, Intraoral Scanner; MIP, Maximum Intercuspal Position; VOR, Virtual Occlusal Record; ICP, Iterative Closest Point; NR, Not Reported; NS, Not Significant

Table 4: Included Studies Grouped by AI Platform

Platform or developer	Studies	Intervention	Direction of the reported findings
Bite-Finder (program for MIP location and collision correction)	Revilla-León *et al.* ×4 [9,10,21,22,]; Ntovas *et al.* [20] (Bite-Finder referenced)	AI-OR; AI-OR plus AI-OCA	Mixed. AI-articulated better than uncorrected IOS in [21]; worse than IOS in [9,10, 22]; more true-positive contacts in [20]
Dentbird (Imagoworks/Dentbird Solutions)	Nagata *et al.* [26]; Win *et al.* [27]	AI-CD	Shorter design time in [26]; equivalent marginal and internal fit but larger occlusal discrepancy in [27]
Scanner-embedded AI-OCA (TRIOS 4/5)	Tian *et al.* [8]	AI-OCA	Improved at some distance bands, reduced at D16–46
Models developed by study authors, or platform not named in the report	Wu *et al.* [23]; Ding *et al.* [24]; Cho *et al.* [25]; Liu *et al.* [28]	AI-OR (Wu); AI-CD (Ding, Cho, Liu)	Descriptive laboratory results only; no common outcome across the four

Results Grouped by AI Platform

Several studies used the same platform, so they cannot be treated as independent evidence about different technologies (Table 4). Four studies by one research group used the Bite-Finder program and a fifth clinical study referred to the same program. Two studies used Dentbird and the remaining studies used scanner software or deep-learning models developed by the study authors or not named in the report.

Read by platform, the Bite-Finder studies point in different directions: AI articulation was better than an uncorrected scanner record in one study, worse than the scanner's own articulation in three and gave more true-positive occlusal contacts in the clinical comparison.

Findings by Intervention

AI-Assisted Crown Design: Win *et al.* [27] compared crowns designed with a generative AI system (GAID, Dentbird Crown) with crowns designed in exocad in 62 patients, each of whom received one crown of each type (124 crowns). Marginal gaps were equivalent on the buccal, mesial and distal surfaces and internal gaps were equivalent. The lingual marginal gap was larger with AI design. Occlusal discrepancy was 149±66 µm for AI-designed crowns and 105±63 µm for conventionally designed crowns. The mean difference (AI minus control) was +43.9 µm (90% CI 38.6 to 49.4), which lies wholly outside the pre-specified equivalence margin of ±15 µm (Figure 2). The 90% interval is the one used for two one-sided equivalence tests. Because it lies entirely above +15 µm, the AI designs were not only non-equivalent but had the larger discrepancy.

Liu *et al.* [28] compared AI-designed zirconia crowns with technician-adjusted digital designs, using 10 crowns per group in the laboratory part and three clinical cases. In the laboratory part the RMS deviation was 13±3 µm (STL comparison) and 18±2 µm (scan comparison) for AI designs, against 45±3 and 120±15 µm for digital designs. In clinical case I the occlusal contact value was −283±36 µm with AI and −184.7±26.5 µm with digital design and the margin gap value was 332±32 µm and 276±25 µm (p = 0.0001 overall). We report these numbers as extracted. Three cases cannot support inference about clinical performance, so this part of the study is descriptive.

Implant crowns (*in vitro*): Cho *et al.* [25] evaluated Deep-Learning (DL)-designed implant crowns on 20 resin casts [25]. Three design workflows were tested: DL automated (no human editing, DB), DL-plus-technician (DM) and conventional CAD (NC). DL-generated crowns (DB) were produced significantly faster than human-designed crowns (p≤0.001). Geometric analyses showed that the DB and DM groups had similar occlusal table areas, cusp angles/heights and emergence profiles to conventional designs (no significant differences, p≥0.16). Only the number/intensity of occlusal contacts differed (p≤0.004) and the authors judged the clinical significance to be minor. The authors concluded that a deep learning-based design approach can attain clinically acceptable functional characteristics of posterior ISCs. Nevertheless, additional tuning by a specialist could enhance some outcomes, such as the crown contour or emergence profile angle [25].

Two further laboratory studies of crown design were small. In Nagata *et al.* [26], five operators designed crowns on two abutment models with an AI program and with conventional CAD. The AI designs took a fraction of the time and had smaller trueness values at both sites (Table 3). The operator count of five limits what this can show. Ding *et al.* [24] trained a 3D-DCGAN on 600 digital casts and tested it on 12. The cusp angle of the AI crowns was closer to that of natural teeth than the biogeneric design, occlusal contact number and area did not differ significantly and the peak stress at 300 N in a finite-element model was 26.73 MPa for the AI crown and 23.97 MPa for the natural tooth.

AI-Based Occlusal Registration

Four studies from the Revilla-León group and one feasibility study examined AI-OR [9,10,21-23]. In the first, AI articulation and corrected scanner records were more accurate than an uncorrected scanner record (trueness p = 0.003, precision p<0.001) [21]. In the other three the scanner's own articulation was more accurate than the AI program overall [9,10,22]. The effect of AI depended on the scanner: it improved the records of iTero and Primescan but reduced those of TRIOS 4 and i700 [22].

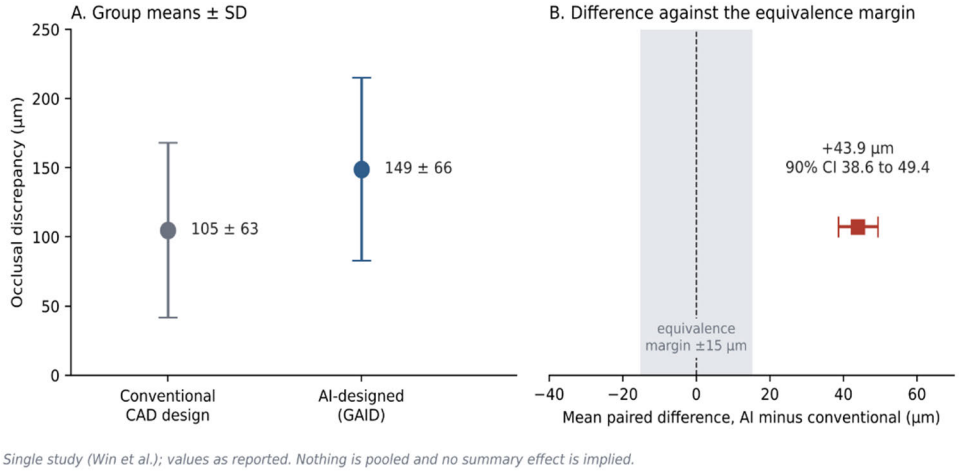

Figure 2: Occlusal Discrepancy in the Paired Clinical Study of Win *et al.* [27] (62 Patients). Panel A shows the group means ± SD (Conventional 105±63 µm; AI-Designed 149±66 µm). Panel B shows the mean Paired Difference (+43.9 µm, 90% CI 38.6 to 49.4) against the ±15 µm Equivalence Margin. This is Single-Study Data and not a Meta-Analytic Estimate

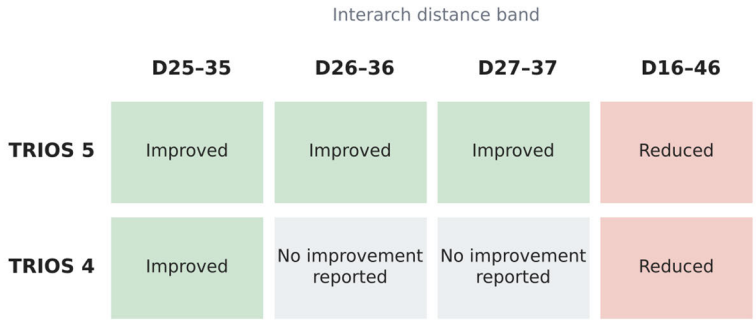

Figure 3: Schematic of the Direction of the AI-OCA effect on Virtual Occlusal Record (VOR) Trueness in Tian *et al.* [8], by Scanner and Interarch Distance Band. It is Illustrative Only, Shows no Magnitudes and must not be Read as a Pooled Estimate

Scan extension and edentulous span also mattered, with complete-arch scans better than half-arch scans and spans of 0 to 2 missing teeth better than 4 [9,10]. None of these four reports gave numerical values in the material extracted (NR). The feasibility study of Wu *et al.* [23] predicted MIP with a deep-learning model and compared it with an iterative-closest-point reference. Mean rotational errors were between 0.730° and 1.407° and translational errors between 0.185 and 1.222 mm in absolute value, with a large standard deviation for rotation about the y axis (8.476°).

AI-Assisted Occlusal Contact Adjustment

Tian *et al.* [8] tested AI-driven Occlusal Contact Adjustment (AI-OCA) with two intraoral scanners [8]. Using partially edentulous typodonts with implants, they generated virtual occlusal records with/without AI correction (n = 4 groups). AI-OCA clearly influenced VOR accuracy in a position-dependent fashion. Occlusal adjustment for TRIOS 5 (TR5) improved trueness at D25-35, D26-36 and D27-37 ($p<0.01$), whereas TRIOS 4 (TR4) exhibited enhancement solely at D25-35 ($p<0.01$). Both scanners exhibited reduced accuracy at D16-46 after AI-OCA ($p<0.01$). Conclusions were that the impact of AI-OCA on VOR accuracy differed depending on the type of scanner and the extent of edentulism [8]. In the only clinical study of this group, Ntovas *et al.* [20] found that AI-registered groups had the highest number of true-positive occlusal contacts and fewer false positives than records without post-processing, but means and standard deviations were not reported. Figure 3 summarises the direction of the AI-OCA effect in Tian *et al.* [8].

Quantitative Synthesis

Heterogeneity precluded meta-analysis. We explain this under the three headings used in the Cochrane guidance. The first is clinical diversity. The studies differ in what was studied (patients, typodonts, stone casts, implant models, digital casts), in the AI tool (Table 4) and in the comparator (technician CAD, scanner articulation, uncorrected scan). The second is methodological diversity. Outcomes were measured on different scales and by different methods: micrometre deviations from a reference scan, film-based contact detection, 36 interlandmark distances, rotation and translation errors, design time in seconds or minutes and finite-element stress. Only two studies were clinical and only one reported a paired difference with a confidence interval. The third is statistical. No common effect measure existed and most laboratory reports gave p-values without means and standard deviations (marked NR in Table 3), so effect sizes and I^2 could not be calculated. Repeated scans of the same casts would also break the independence assumption of a pooled estimate. Within each intervention group, no outcome was reported with usable data by three or more studies. We therefore describe each study's own results and we did not test statistical heterogeneity. Figures 2 and 3 show single-study results and are not pooled.

Figure 2 shows the data of Win *et al.* [27] only: the two group means with their standard deviations and the paired difference against the equivalence margin. It is not a forest plot and implies no summary effect. Figure 3 is a schematic of the direction of the AI-OCA effect reported by Tian *et al.* [8]; it plots no magnitudes.

Risk of Bias

The two clinical studies were rated at serious risk of bias with ROBINS-I (Table 5 and 6). Neither randomized allocation and neither blinded the clinician or the outcome assessor. Win *et al.* [27] used a within-patient paired design, which controls patient-level confounding and reported its results in full against a pre-specified equivalence margin. Ntovas *et al.* [20] enrolled a convenience sample of volunteers without a pre-specified power calculation and did not report means and standard deviations.

The laboratory studies were all rated at moderate risk and none reached the low-risk category, mainly because none described a blinded assessor and sample sizes were modest. Three studies [23,25,28] sat exactly on the 70% boundary. Few studies gave an a priori power calculation, so a non-significant result in these studies should be read as possibly underpowered and not as evidence of equivalence.

Table 5: Risk of Bias of the Laboratory Studies (adapted QUIN)

Study	Randomisation	Blinding	Control group	Sample adequacy	Outcome reporting	Confounding	Score	Overall
Tian *et al.* [8]	N/A	0	2	1 (n NR)	2	1	6/10 (60%)	Moderate
Revilla-León *et al.* [21]	N/A	0	2	1 (15)	2	1	6/10 (60%)	Moderate
Revilla-León *et al.* [22]	N/A	0	2	1 (10)	2	1	6/10 (60%)	Moderate
Revilla-León *et al.* [9]	N/A	0	2	1 (10)	2	1	6/10 (60%)	Moderate
Revilla-León *et al.* [10]	N/A	0	2	1 (10)	1	1	5/10 (50%)	Moderate
Wu *et al.* [23]	N/A	0	2	2 (25 test)	2	1	7/10 (70%)	Moderate
Ding *et al.* [24]	N/A	0	2	1 (12 test)	2	1	6/10 (60%)	Moderate
Cho *et al.* [25]	N/A	0	2	2 (20)	2	1	7/10 (70%)	Moderate
Nagata *et al.* [26]	N/A	0	2	0 (5 operators)	2	1	5/10 (50%)	Moderate
Liu *et al.* [28]	N/A	1	2	1 (10 + 3 cases)	2	1	7/10 (70%)	Moderate

Domain scores: 2 = adequately reported and addressed; 1 = partly or unclear; 0 = not reported or inadequate; N/A = domain not applicable and excluded from the denominator. Overall score = sum of domain scores ÷ (2 × applicable domains) × 100. Low risk >70%; moderate 50-70%; high <50%. Blinding was scored 0 when the report did not describe a blinded assessor, although automated software measurement is less open to assessor bias. Sample adequacy: 2 = a priori calculation or ≥20 independent units per group; 1 = 10-19 units or no information; 0 = <10 units (units shown in brackets)

Table 6: Risk of Bias of the Clinical Studies (ROBINS-I)

Study	Confounding	Selection of participants	Classification of interventions	Deviations from intended interventions	Missing data	Measurement of outcomes	Selection of reported result	Overall
Win *et al.* [27]	Moderate	No information	Low	Low	Low	Serious	Low	Serious
Ntovas *et al.* [20]	Serious	Serious	Low	Low	No information	Serious	Moderate	Serious

The overall rating follows the most severe domain. Measurement of outcomes was rated serious because neither study blinded the outcome assessor

DISCUSSION

This review identified limited but emerging evidence on AI-assisted occlusal design and adjustment in prosthodontics. The evidence is mostly technical: nine of the twelve studies were laboratory studies, one more was a laboratory study with three clinical cases, two were comparative clinical studies, none was randomised and none followed patients over time. Laboratory accuracy should not be read as clinical efficacy and the findings below are phrased with that in mind.

AI-Assisted Crown Design

AI-based CAD/CAM systems can achieve crown fits comparable to conventional methods, with some caveats. In clinical settings, generative-AI-designed crowns had similar marginal adaptation on most surfaces but tended to have larger occlusal gaps [27]. Similarly, in the laboratory, DL-designed implant crowns matched human designs in occlusal geometry [25] and the two laboratory studies that timed the work found much shorter design times with AI [25,26]. Results were not uniformly in favour of AI, however and AI design did not automatically outperform expert planning [27,28].

The most clinically informative crown fit data in this review come from Win *et al.* [27], who used an equivalence testing framework with a pre-specified margin of ±15 µm. AI-designed crowns produced a mean occlusal discrepancy of 149±66 µm compared with 105±63 µm for conventionally designed crowns, yielding a mean difference of +43.9 µm (90% CI 38.6-49.4 µm). Because the confidence interval lies entirely outside the ±15 µm equivalence zone, the AI method was statistically non-equivalent to the conventional approach for occlusal fit, a finding that must be interpreted carefully.

Statistical and clinical significance are different questions here. There is no consensus threshold for occlusal discrepancy. A marginal gap of up to 120 µm is the figure usually cited as clinically acceptable for cement film thickness [29] and some authors use a figure near 150 µm as a working benchmark for occlusal discrepancy, but we found no consensus source for the latter and treat both as benchmarks and not as standards. Both group means in Win *et al.* [27] are below 150 µm, but the mean of the AI group (149 µm) sits right at it. With a standard deviation of about 66 µm and assuming roughly normal distributions, which the report does not confirm, about half of the AI-designed crowns would exceed 150 µm against about a quarter of the conventional ones. The difference is also not small in relative terms: it is about 42% of the conventional mean and about 0.7 of a pooled standard deviation (calculated from the reported means and SDs, ignoring the pairing).

What this difference means for patients was not measured. Occlusal contacts are mechanically sensitive and it is plausible that an excess of this size could produce premature contacts, call for more chairside grinding or raise stress at the cement interface or margins. These are potential implications and not findings of this review, because the included clinical study did not assess them. No study followed patients beyond the seating or scanning visit, so the long-term consequences of a systematic occlusal excess are unknown. Until the algorithms are refined, it seems prudent for clinicians who use generative design systems to verify occlusion at seating as routinely as they would for any other design.

AI-Based Registration and Contact Adjustment

The *in vitro* study of virtual occlusal records showed that AI-OCA yields mixed results. It improved the trueness of maxillomandibular registration at some interarch distances, especially with the newer scanner (TRIOS 5), but reduced it at others (D16-46) [8]. The Bite-Finder studies were similarly mixed [9,10,21,22]. One possible explanation, which these data cannot test, is that AI algorithms may optimise global arch relationships while

introducing errors over short spans. If that were true, AI-OCA might reduce digital occlusal collisions in extensive cases but add error in solitary restorations. We offer this as a hypothesis that needs clinical validation and not as a recommendation for practice [20,12].

Crown Design and Occlusal Adjustment are Different Interventions

Combining them can hide differences that matter. AI-CD changes the shape of the restoration before it is made, so an error is built into the crown and shows up as a systematic occlusal excess, as in Win *et al.* [27] AI-OR and AI-OCA change the digital occlusal relationship on which the restoration is designed, so an error affects every restoration planned from that record and it may be small per tooth but shared across an arch. Post-delivery adjustment, which no included study examined, removes material from a restoration already in the mouth and cannot be reversed. A clinician therefore has different checks available in each case and the clinical risks do not transfer from one to another. The evidence we found speaks mainly to the first two.

One Platform, One Group

Four studies came from one research group and used one program and a fifth referred to the same program (Table 4). Grouped by platform, the evidence is thinner than a count of twelve studies suggests: it is mainly about Bite-Finder, Dentbird and one scanner's embedded software. Positive or negative findings for one platform cannot be carried over to others.

Heterogeneity and limitations: Studies varied widely in design and outcomes, precluding meta-analysis. Sample sizes were small and most data came from laboratory simulations. Only one within-subject clinical study that tested a crown design was identified and it was non-randomised and not blinded, limiting confidence. The other clinical study compared scan post-processing methods. In vitro results may not translate directly to patient care. Outcome measures were diverse (3D deviation values, visual scores, treatment times) and standardized thresholds for success are lacking [13].

CONCLUSION

The current evidence on AI-assisted occlusal design and adjustment addresses technical accuracy at the time of fabrication. It does not show whether these tools improve restoration survival, patient comfort or function over time. In one clinical study, AI-assisted crown design gave fit values comparable to conventional design on most marginal and internal measures but a larger occlusal discrepancy and in laboratory studies it shortened design time. Results for AI-based registration and contact adjustment were mixed and depended on the scanner, the distance measured and the edentulous span. Overall, AI shows potential to augment general dentistry, but current studies are preliminary. Until more robust data are available, clinicians should apply AI-assisted occlusal technologies judiciously and continue to rely on clinical judgment for final adjustments. Randomised controlled trials with standardised outcome sets and follow-up of at least three years are needed before these tools can be considered ready for broad implementation.

Limitations

The limitations of the evidence are those above: few clinical studies, small samples, laboratory designs, no randomisation, no follow-up and heterogeneous AI technologies and outcomes. The limitations of the review process are the following. Only English-language articles were included, so relevant studies in other languages may have been missed. We did not search grey literature, preprints, registries, dissertations or conference proceedings and we searched three databases (Embase and Web of Science were not searched), so publication bias is possible and could not be assessed with a funnel plot because no pooled analysis was done. The review was not registered, so we cannot show that the methods were fixed before the results were known. Three of the ten laboratory scores sit exactly on the 70% boundary between moderate and low risk and the QUIN criteria were grouped into six domains for this review. Many laboratory reports did not give means and standard deviations, so the results table is partly qualitative. Finally, studies cluster around a small number of platforms and one research group, as described above.

Implications for practice and research: AI tools show promise in enhancing efficiency and consistency of prosthetic design [25,30]. For example, automated occlusal algorithms can eliminate digital interferences, potentially reducing the time required for clinical adjustments. A fundamental limitation of the available evidence is the complete absence of long-term clinical outcomes. None of the twelve included studies reported prosthesis survival rates, ceramic fracture incidence, occlusal wear indices, temporomandibular joint symptoms, or formally validated patient satisfaction measures. This is not a minor methodological gap; it is the central reason why any clinical translation of the present findings must be approached with caution. Fit accuracy measured on typodont casts or in short-term clinical trials does not reliably predict whether a restoration will remain functional and comfortable over three to five years of clinical service. Future prospective studies should be designed with a minimum follow-up of three years and should incorporate standardised outcome domains, including annual occlusal wear mapping, validated chewing performance assessments, Patient-Reported Outcome Measures (PROMs) such as the Oral Health Impact Profile (OHIP-14) and structured recording of technical complications including fracture, debonding and the need for occlusal readjustment. Studies should also report means, standard deviations and the unit of analysis, state whether specimens are independent and cover more than one AI platform.

Only evidence of this kind will allow a meaningful judgement on whether AI-assisted workflows translate laboratory-level accuracy gains into measurable patient benefit. Taken together, the evidence should be regarded as hypothesis-generating and not practice-defining. It provides a rationale for well-designed prospective clinical trials but does not in itself justify routine adoption of AI-assisted occlusal design or adjustment in clinical prosthodontic practice.

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Supplementary Table S1: Search Strategies

Database	Search string	Filters
PubMed	("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh] OR "Deep Learning"[Mesh] OR "artificial intelligence"[tiab] OR "machine learning"[tiab] OR "deep learning"[tiab] OR "neural network*"[tiab] OR generative[tiab]) AND ("Dental Occlusion"[Mesh] OR "Dental Prosthesis"[Mesh] OR "Crowns"[Mesh] OR "Computer-Aided Design"[Mesh] OR occlusion[tiab] OR occlusal[tiab] OR "occlusal adjustment"[tiab] OR "digital occlusion"[tiab] OR "intercuspal position"[tiab] OR "crown design"[tiab] OR "dental prosthesis"[tiab] OR prosthodontic*[tiab] OR "CAD/CAM"[tiab])	Publication date 2015/01/01 to 2025/12/31; language English
Scopus	TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR generative) AND (occlusion OR occlusal OR "occlusal adjustment" OR "digital occlusion" OR "intercuspal position" OR "crown design" OR "dental prosthesis" OR prosthodontic* OR "CAD/CAM"))	PUBYEAR>2014 AND PUBYEAR<2026; LANGUAGE (english)
Cochrane Library (CENTRAL)	#1 MeSH descriptor: [Artificial Intelligence] explode all trees; #2 ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR generative):ti,ab,kw; #3 #1 OR #2; #4 MeSH descriptor: [Dental Occlusion] explode all trees; #5 MeSH descriptor: [Dental Prosthesis] explode all trees; #6 (occlusion OR occlusal OR "occlusal adjustment" OR "digital occlusion" OR "intercuspal position" OR "crown design" OR "dental prosthesis" OR prosthodontic* OR "CAD/CAM"):ti,ab,kw; #7 #4 OR #5 OR #6; #8 #3 AND #7	Publication year 2015 to 2025; English

Search date: [DD Month YYYY]. The strings above were written from the search terms reported in the Methods; replace them with the exported search history from each database if they differ