

Artificial Intelligence in Facial Analysis and Treatment Planning for Orofacial Harmonization: Accuracy, Bias and Clinical Integration in Dental Practice — A Narrative Review

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Abstract

Background: Artificial intelligence (AI) is rapidly entering aesthetic practice through facial analysis, three-dimensional (3D) scanning, outcome simulation and patient communication tools. Dentistry already works within a mature digital workflow (intraoral scanning, cone-beam computed tomography, digital smile design), which makes it a natural setting for AI-assisted facial planning in orofacial harmonization. Whether these tools are accurate, fair and safe enough for clinical decisions, however, remains uncertain.

Materials and Methods: A narrative review was conducted in PubMed/MEDLINE (2021 to October 2026) using combinations of the terms artificial intelligence, deep learning, machine learning, facial aesthetics, facial attractiveness, facial landmark, 3D facial scanning, smile design and injectables. Systematic reviews, clinical and validation studies, and studies of bias and patient perception were prioritized and synthesized qualitatively.

Results: Systematic reviews report that AI improves diagnostic accuracy, prediction, counseling and planning in facial aesthetic surgery, although study quality varies. 3D facial scanning is generally accurate for midline landmarks but less reliable laterally and is influenced by smile line, facial hair, head position and device type. A deep-learning model located 34 3D soft-tissue landmarks with a mean error of 1.80 mm, but errors reached 4.39 mm in subjective and cheek landmarks. AI attractiveness models trained on single-ethnicity datasets approximate human ratings, while commercial platforms scored White faces higher than Black faces by 1.27 points. Deep-learning prediction of postrestorative facial appearance and AI-generated smile designs show promising concordance with real or manual results. Consumers report that AI visualization would increase their trust in practitioners, which also raises the risk of unrealistic expectations.

Conclusion: AI should function as clinical decision support rather than as an autonomous arbiter of beauty. A human-in-the-loop framework with checkpoints for data acquisition, landmark verification, bias awareness, expectation management and privacy is proposed for dental practices adopting AI-assisted orofacial harmonization.

Key Word: artificial intelligence; deep learning; facial analysis; 3D facial scanning; orofacial harmonization; smile design; algorithmic bias.

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I. Introduction

Aesthetic medicine combines clinical expertise with artistic judgment, and artificial intelligence (AI) is now being introduced into both components. Recent reviews describe applications in facial analysis, robotic-assisted procedures, predictive outcome modeling and personalized treatment planning, alongside persistent concerns about biased training data, opaque decision-making and inconsistent regulation [1]. A systematic review of 66 studies on AI and machine learning in facial aesthetic surgery concluded that these tools improve diagnostic accuracy, predictive capability, patient counseling and treatment planning, with 63.6% of studies rated of good quality [2]. Generative AI now allows both consumers and clinicians to visualize treatments before they are performed [3], and AI-driven skin analysis and 3D facial reconstruction have already been incorporated into many cosmetic practices [4].

Patient demand is moving in the same direction. In a 2026 industry report combining a consumer survey with search-trend data, 84% of respondents said that AI-generated insights into procedures such as botulinum toxin and filler injections would increase their confidence before treatment, and 87% said that AI visualization would improve their trust in a practitioner; online interest in “micro-injections” rose by more than 850% in one year [5]. These figures come from a commercial source and should be interpreted cautiously, but they illustrate the expectations patients now bring to consultations.

Dentistry is in a particular position. Intraoral scanners, cone-beam computed tomography (CBCT), virtual planning and 3D printing are already routine in prosthodontics, orthodontics, implantology and maxillofacial surgery [6], and AI is increasingly embedded in orthodontic workflows such as clear aligner therapy [7] and in dental practice management [8]. Orofacial harmonization, the coordinated aesthetic treatment of the smile, lips and lower face, sits at the junction of these workflows and of aesthetic medicine. This narrative review examines the accuracy of AI-supported facial acquisition and analysis, its use in prediction and simulation, its integration into the dental digital workflow, and the ethical risks of bias, unrealistic expectations and privacy, and proposes a practical framework for its responsible use.

II. Materials and Methods

This is a narrative review. PubMed/MEDLINE was searched from 2021 to October 2026 with combinations of the terms artificial intelligence, deep learning, machine learning, facial aesthetics, facial attractiveness, facial landmark, facial age, 3D facial scanning, stereophotogrammetry, smartphone facial scanner, smile design, injectables and bias. Systematic and scoping reviews, validation and clinical studies, and studies on

algorithmic bias and patient perception were prioritized. One industry report on consumer attitudes and the U.S. federal de-identification standard were added for context. Findings were synthesized qualitatively, as heterogeneity in devices, algorithms, reference standards and outcome metrics precluded meta-analysis.

III. Acquiring the Face: 3D Scanning as the Data Foundation

Every AI facial analysis is limited by the quality of the data it receives. A 2026 systematic review of 18 studies (498 participants) found that most 3D facial scanning modalities achieve clinically acceptable landmark accuracy and repeatability under standardized conditions, with stereophotogrammetry and structured-light systems performing most consistently; smartphone-based systems were promising but more variable, especially for lateral landmarks, and midline landmarks were consistently more reproducible than lateral ones [9].

Recent clinical studies show how sensitive this step is to apparently minor variables. When facial scans were merged with intraoral scans to build virtual patients, the patient's smile line and the registration method significantly affected trueness, and smartphone-based and professional scanners required different integration protocols [10]. Facial hair influenced the accuracy of virtual patients built from smiling scans, and a dedicated beard-scanning mode improved accuracy for full beards but worsened it for stubble [11]. With an app-based smartphone scanner, both head position and the viewing angle of the device changed the accuracy of the automatically generated true horizontal plane [12], and the design of the virtual facebow fork interacted with the scanner type [13]. Table 1 summarizes these sources of error.

Table 1. Sources of error in 3D facial acquisition that propagate into AI-assisted analysis

Variable	Reported effect	Practical implication
Scanner technology	Stereophotogrammetry and structured light most consistent; smartphones variable, especially laterally [9]	Match the device to the decision; verify lateral measurements
Smile line and registration	Medium smile line and certain registration sequences reduce trueness [10]	Standardize smile capture; add a retracted scan when indicated
Facial hair	Affects accuracy of smiling scans; beard mode helps only with full beards [11]	Record facial-hair status; repeat scans under the same condition
Head position and viewing angle	Alter accuracy of automatically located reference planes [12]	Use natural head position and a level capture angle
Registration accessories	Virtual facebow design interacts with scanner type [13]	Validate the full chain, not the scanner alone

For orofacial harmonization, these findings have a direct consequence: the lips and perioral region are dynamic, change with smile line and expression, and are exactly where standardization is hardest. Longitudinal comparisons, such as monitoring facial volume loss in patients losing weight, where radiographic studies have quantified midfacial deflation of about 7% per 10 kg [14], are only meaningful if the acquisition protocol is held constant.

IV. Automated Analysis: Landmarks, Indices and Attractiveness Scores

A. Landmark detection

Automated landmarking is the first analytical step that AI can accelerate. A deep-learning facial soft-tissue network trained on 297 cases detected 34 3D landmarks with a mean radial error of 1.80 mm; for the 28 landmarks with high operator reproducibility the error was 1.25 mm, whereas the six landmarks dependent on subjective judgment had an average error of 4.39 mm [15]. By region, lip landmarks were the most accurate (1.03 mm) and bilateral cheek landmarks the least, and agreement between manual and automated measurements was high (mean intraclass correlation 0.909) [15]. The authors themselves conclude that clinician verification remains mandatory for lateral facial regions [15], which mirrors the acquisition limitations described above.

B. Aesthetic indices and attractiveness scoring

Beyond geometry, AI has been used to generate summary indices such as a Facial Aesthetic Index and a Facial Youthfulness Index [16] and to predict perceived attractiveness. In orthodontics, a ResNet-50 model trained on 1,500 Caucasian faces from a public dataset approximated human attractiveness ratings with a mean absolute error of 0.215 on a 5-point scale, but performance varied across score ranges, and the authors explicitly called for training on diverse populations [17]. When multimodal large language models were compared with orthodontists, maxillofacial surgeons and laypersons in rating standardized profile modifications, human-AI agreement depended on the model and on the sex of the face, and both AI systems declined to give surgical recommendations

because of built-in ethical restrictions [18]. These studies show that AI can reproduce the average judgment encoded in its training data, which is precisely why the composition of that data matters.

V. Prediction and Simulation: From Smile Design to Facial Outcome

Digital smile design was among the first dental applications of AI. A scoping review found that AI-generated smile designs were not significantly different from manually created designs in aesthetic perception, and that 3D designs were more accurate than 2D ones, although only four eligible studies were identified [19]. Prediction is now extending from the teeth to the face. A bidirectional deep-learning model trained on pre- and postrestorative 3D facial scans of edentulous patients predicted postrestorative facial morphology with mean landmark errors of 3.80 to 5.98 mm; accuracy was best at the nasal tip (2.17 mm) and worst at the left commissure (6.88 mm), and expert reviewers rated visual concordance at 4.2 of 5 [20]. For orofacial harmonization, this line of research is especially relevant, because changes in tooth position, vertical dimension and lip support alter the soft tissues that injectable treatment aims to modify. A prosthodontic or orthodontic plan that predicts lip support can therefore inform, and sometimes replace, a planned filler treatment.

Simulation, however, has a well-recognized downside. A systematic review of AI in aesthetic plastic surgery warned that patients may see an AI-generated image they like that is impossible to achieve, and recalled the adage of under-promising and over-delivering [21]. In the injectable setting, simulation also cannot represent vascular anatomy or the risk of vascular occlusion, which remains the most feared filler complication and requires emergency protocols independent of any planning software [22].

VI. Integration with the Dental Digital Workflow

The dental team already manages the data types that AI-assisted facial planning requires: intraoral scans, facial scans, CBCT volumes and photographs. Virtual surgical planning and 3D printing are established in the management of facial fractures [6], and AI-supported monitoring and treatment planning are part of contemporary aligner therapy [7]. Integrating facial analysis into this chain allows the clinician to plan teeth, lips and lower face as a single unit, to communicate the plan visually, and to follow the result over time. At the practice level, AI adoption is also part of a broader strategy of innovation and economic sustainability in U.S. dental practice management, which includes teledentistry and data-driven operations [8]. The barrier is less technological than organizational: standardized capture protocols, staff training and a clear allocation of responsibility for verifying AI outputs.

VII. Measuring Outcomes: What AI Can and Cannot Capture

AI has been proposed as an objective outcome measure. Facial expression analysis software detected an increase in the “happy” emotion from 1.03% to 13.17% and a fall in the “angry” emotion from 14.66% to 0.63% after facelift surgery in 15 patients [23]. AI facial age estimation, however, has given inconsistent results: in 27 orthognathic surgery patients, AI-estimated age did not change after surgery even though social appearance anxiety improved, leading the authors to conclude that validated, repeatability-tested tools are needed before such estimates serve as primary outcomes [24]; in a small dermatologic pilot, automated age estimation simply tracked chronological age [25]. Machine learning has also been used to analyze the questions patients ask before and after injectable procedures [26]. Together, these studies suggest that AI metrics should complement, not replace, validated patient-reported outcome measures such as the FACE-Q [27].

VIII. Bias, Beauty Standards and Expectation Management

The most serious ethical concern is that AI may encode a narrow, Eurocentric standard of beauty. In a 2026 study, five publicly available AI facial-rating platforms scored 120 standardized AI-generated female faces; White faces received the highest mean score (8.18), followed by Asian (7.79), Latino (7.72) and Black faces (6.91), and the difference between White and Black faces was 1.27 points [28]. Even carefully developed academic models are often trained on single-ethnicity datasets [17]. In the United States, where patients are highly diverse and where lower-face aesthetics and aging patterns vary across ethnic groups, such bias can push treatment toward homogenized features that patients may not want and that clinicians may not consciously choose.

Social media amplifies these effects. Algorithm-driven platforms shape trends in cosmetic facial treatment [29], and AI simulation can turn those trends into concrete, personalized images. The clinician’s task is therefore to use AI to support a conversation about the patient’s own features, identity and goals, and not to let a score or a filtered simulation define what the patient “should” look like [1,21].

IX. Privacy, Transparency and Accountability

Facial images are among the most sensitive health data. Under the U.S. HIPAA de-identification standard, full-face photographic images and comparable images are listed among the identifiers that must be removed for data to be considered de-identified [30]. When patient scans are uploaded to cloud-based AI

platforms, practices must know where the data are stored, whether they are used to train vendor models, and what the patient has consented to. More broadly, reviews of AI in clinical medicine identify data privacy, algorithmic bias and the “black-box” nature of many models as the main barriers to adoption, and point to explainable AI as a partial solution [1,31]. Responsibility for the final plan, and for any complication, remains with the licensed clinician.

X. A Human-in-the-Loop Framework for Dental Practice

Based on the evidence reviewed, Table 2 proposes five checkpoints for dental practices that adopt AI-assisted facial analysis for orofacial harmonization.

Table 2. Proposed human-in-the-loop checkpoints for AI-assisted orofacial harmonization

Checkpoint	Clinical action	Evidence base
1. Acquisition	Standardized protocol (device, head position, smile line, facial hair); repeat under identical conditions for follow-up	[9-12]
2. Verification	Clinician checks automated landmarks, especially lateral and subjective points	[15]
3. Bias awareness	Know the training population of the tool; avoid attractiveness scores as treatment targets	[17,28]
4. Expectation management	Present simulations as possibilities, not promises; document consent; pair with PROMs	[21,27]
5. Privacy and safety	Vendor data policies, consent for image use; complication protocols independent of software	[22,30]

XI. National Interest and Significance

AI-based facial tools are reaching U.S. consumers directly, often before any clinician is involved [3,5]. If these tools are biased [28] or produce unattainable simulations [21], their effects extend beyond individual consultations to population-level beauty norms and to patient safety in a rapidly expanding injectable market. Dentistry can contribute a disciplined, evidence-based model of AI use because it already operates validated digital workflows, standardized imaging and a culture of measurement in millimeters and degrees. Developing professional guidance on AI-assisted facial planning, requiring diverse training datasets, and including AI-related privacy and bias content in continuing education would help ensure that these technologies improve rather than distort aesthetic care for the diverse U.S. population.

XII. Limitations and Research Agenda

This review is narrative and does not provide a quantitative synthesis. Many included studies are small, single-center, retrospective or conducted in vitro or with AI-generated images, and some commercial data were drawn from an industry report [5]. Research is needed on: external validation of facial landmarking and prediction models in diverse U.S. populations; prospective studies testing whether AI-assisted planning improves objective and patient-reported outcomes of orofacial harmonization; the effect of AI simulation on patient expectations and satisfaction; integrated models that predict the combined soft-tissue effect of dental and injectable treatment [20]; and auditing standards for bias in commercial aesthetic AI [28].

XIII. Conclusion

Artificial intelligence can make facial analysis faster, more reproducible and easier to communicate, and the dental digital workflow provides a natural home for its integration into orofacial harmonization. The current evidence, however, shows that accuracy depends heavily on standardized acquisition, that automated landmarks remain least reliable in the lateral and subjective regions, that attractiveness models can encode ethnic bias, and that simulations may create expectations no treatment can meet. AI should therefore be used as clinical decision support within a human-in-the-loop framework, never as an autonomous judge of beauty. Used in this way, it can strengthen, rather than replace, the clinical judgment, ethical sensitivity and anatomical knowledge on which safe aesthetic care depends.

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