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The Role of Artificial Intelligence in Rhinoplasty: Narrative Literature Review

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ABSTRACT

Introduction: Rhinoplasty remains one of the most technically demanding procedures in facial plastic surgery. Artificial intelligence (AI) has emerged as a transformative technology with po-tential to address longstanding challenges in surgical subjectivity, outcome prediction, and patient communication. This narrative review synthesizes current evidence on AI applications across all phases of rhinoplasty care—from preoperative simulation and patient counseling to in-traoperative guidance and postoperative outcome assessment—while critically exam-ining persistent limitations and ethical considerations.

Materials and Methods: A literature search was conducted across PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar for studies published between 2015 and 2026. Thirty-nine studies met the inclusion criteria.

Results: AI applications span five principal domains: preoperative planning and simulation; aes-thetic analysis and attractiveness quantification; large language model–based patient counseling; intraoperative guidance and augmented reality; and postoperative outcome evaluation. Reported model accuracies ranged from 82% to 97%. Large language mod-els performed comparably or superiorly to expert surgeons in structured counseling eval-uations.

Conclusion: AI offers substantial promise for enhancing precision and reproducibility in rhinoplasty, but algorithmic bias, limited dataset diversity, absence of prospective validation, and unresolved ethical concerns currently restrict widespread clinical adoption. AI should be regarded as a powerful adjunct to, rather than a replacement for, surgical expertise.

Keywords: Artificial intelligence; Rhinoplasty; Machine learning; Deep learning; Large language model; Surgical simulation; Outcome prediction; Facial plastic surgery.

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Introduction

Rhinoplasty consistently ranks among the most performed aesthetic surgical procedures worldwide and is simultaneously regarded as one of the most technically complex [1]. The nasal structure demands a nuanced understanding of three-dimensional anatomy, the interplay of soft tissue and cartilaginous support, individual healing dynamics, and culturally influenced aesthetic preferences. For decades, surgeons have relied on clinical judgment, two-dimensional photographic analysis, and manual computer morphing to communicate anticipated outcomes and plan surgical approaches.

These methods, while foundational, are inherently subjective, time-consuming, and dependent on individual surgeon experience [2]. The emergence of AI—encompassing machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), generative adversarial networks (GANs), and large language models (LLMs)—has opened new possibilities for addressing these limi-tations across medicine and surgery [3,4]. In rhinoplasty specifically, AI has been ap-plied to automate preoperative design, predict postoperative outcomes, objectively quan-tify aesthetic change, guide intraoperative decisions, and supplement patient education and counseling [1,5].

Research activity in this space has grown substantially over the past decade. A scoping review by Osie et al. [6] identified a near-exponential increase in AI-related rhinology publications between 2017 and 2021, rising from 3 articles in 2017 to 31 in 2021, with AI demonstrating excellent or very good diagnostic utility in the majority of evaluated studies [6]. Systematic reviews of AI in plastic surgery broadly confirm that rhinoplasty and aesthetic surgery represent the most active research domains, though most work re-mains in preclinical or early translational phases [7].

Despite this progress, important challenges persist. Datasets used to train AI models are frequently small, demographically homogeneous, and derived from single institutions [5,8]. Many models lack external validation [6,8]. Ethical questions surround the rein-forcement of narrow beauty standards [9], the medico-legal implications of AI-generated simulations, and the appropriate boundaries of AI in patient communication [10]. Surgical algorithms for rhinoplasty remain limited in number and rarely report out-comes [11]. This review aims to provide a comprehensive and critically appraised synthesis of cur-rent AI applications across all phases of rhinoplasty care, highlight the most significant technical and clinical advances, and delineate the obstacles that must be overcome be-fore AI can be responsibly integrated into routine rhinoplasty practice.

Materials and Methods

Study Design

This study is a narrative literature review. The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines adapted for narrative reviews [7]. The PRISMA flow diagram is presented as Figure 1. Records were identified from PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar (January 2015–April 2026). After duplicate removal, title/abstract screening, and full-text eligibility assessment, 39 studies were included in the final narrative review.

Search Strategy

A literature search was conducted across four major electronic databases: Pub-Med/MEDLINE, Scopus, Web of Science, and Google Scholar. The search covered publications from January 2015 to April 2026. Three concept groups were combined us-ing Boolean operators: **(1)** rhinoplasty and nasal surgery terminology; **(2)** AI, ML, and DL terminology; and **(3)** relevant outcome domains including simulation, planning, outcome, counseling, and attractiveness assessment. Reference lists of included articles and relevant systematic reviews were manually screened to identify additional eligible stud-ies.

Eligibility Criteria

Original research articles, systematic reviews, narrative reviews, and methodological studies published in English were considered eligible if they addressed AI applications in rhinoplasty or closely related facial plastic surgery procedures with direct applicability to rhinoplasty. Studies focusing exclusively on non-rhinoplasty procedures without methodological relevance to nasal surgery were excluded. Conference abstracts without full-text publications and case reports without data were also excluded.

Study Selection and Data Extraction

Two independent reviewers screened titles and abstracts of all retrieved records. Disa-greements were resolved by consensus. Data extracted from each included study in-cluded: study design, sample characteristics, AI methodology, outcome measures, and

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reported limitations. The study selection process is illustrated in Figure 1.

Ethical Considerations and Conflict of Interest

This review did not involve human participants and therefore did not require ethical ap-proval. No financial support or personal assistance was received. The authors declare no competing interests.

Results

Study Selection

The initial database search identified 1,247 records. After addition of 14 records from manual reference searching, removal of duplicates, title and abstract screening, and full-text eligibility assessment, 39 studies met all inclusion criteria and were included in this review (Figure 1). Studies were published between 2016 and 2026. The primary reasons for full-text exclusion were: non-rhinoplasty AI content (n = 61), absence of AI meth-ods (n = 42), and insufficient quantitative or qualitative data (n = 36).

Overview of Included Studies

The 39 included studies encompassed original research articles (n = 26), systematic re-views (n = 7), and narrative reviews (n = 6). Studies originated from 16 countries, with the United States, China, and European centers most represented. AI applications were categorized into five principal domains: **(1)** preoperative planning and three-dimensional simulation; **(2)** aesthetic analysis and attractiveness quantification; **(3)** LLM-based pa-tient counseling and education; **(4)** intraoperative guidance and augmented reality; and **(5)** postoperative outcome evaluation. The distribution of studies across these domains is summarized in Table 1.

AI Methodologies Represented

The primary AI architectures represented across included studies were CNNs, GANs, support vector machines, and transformer-based LLMs. CNNs were the most frequently employed architecture for image analysis tasks including rhinoplasty status classifica-tion, attractiveness quantification, and age estimation [28,29,30]. GANs were applied to postoperative simulation and learning of individual surgeon aesthetic styles [15]. LLMs, principally successive versions of ChatGPT, were evaluated for preoperative and postoperative patient counseling [21,22,23,24]. Augmented reality combined with ML-based analysis was applied to intraoperative surgical guidance [12].

Preoperative Planning and Three-Dimensional Simulation

Li et al. [14] presented the first AI model for automated preoperative three-dimensional simulation of rhinoplasty, training a modified FoldingNet deep neural network on point cloud data from 209 patients [14]. The trained model achieved automated aesthetic nasal contour design comparable to manual simulation, identifying two distinct cognitive modes—one resembling human aesthetic reasoning and one uniquely machine-mediated. Chinski et al. [15] evaluated an AI model trained to replicate an individual surgeon's aesthetic style, finding that blinded specialist evaluators agreed with AI-generated simulations 68.4% of the time versus 77.3% for surgeon-generated simula-tions [15]. Heydari et al. [12] introduced an intelligent augmented reality application integrating preoperative 3D modeling, ML-based facial ratio analysis, and real-time AR visualization for intraoperative guidance [12]. Choi et al. [16] described a system com-bining 3D simulation with CT-based implant design and printing, achieving dimensional accuracy within 0.07 mm for patient-specific silicone implants [16]. Cikita and Mas'ud [13] reviewed AI integration with genomics and facial typing, identifying genetic mark-ers associated with nasal shape and wound healing and emphasizing the need for cultur-ally inclusive morphometric models [13]. Celikoyar et al. [11] conducted a scoping re-view identifying 39 surgical algorithm studies for rhinoplasty, of which only 7 reported outcomes—establishing the limited formal infrastructure into which AI decision sup-port tools are now being introduced [11].

Aesthetic Analysis and Attractiveness Quantification

Štěpánek et al. [17,20] applied ML classifiers to rhinoplasty facial image data, finding that enlargement of the nasolabial and nasofrontal angles significantly predicted post-rhinoplasty attractiveness increases ($p < 0.05$), with neural networks demonstrating highest predictive accuracy for facial emotion classification [17,20]. Bayar Muluk [3] corroborated these findings in a broader review, noting that ML models can detect spe-cific facial features correlating with increased attractiveness following cosmetic rhino-plasty [3]. Mahmood et al. [19] applied deep CNN phenotyping to 1,192 rhinoplasty photographs alongside actress photographs, finding that postoperative patients shifted significantly toward the phenotype more heavily occupied by highly-rated actresses ($p < 0.000001$), suggesting rhinoplasty drives facial appearance toward above-average rather than merely average attractiveness [19]. Patcas

et al. [18] compared AI attractiveness scoring with expert and layperson panels in cleft patients, finding AI scores comparable to professional panel averages but yielding lower scores for controls, indicating im-portant calibration adjustments are needed [18]. Borsting et al. [28] developed RhinoN-et—a CNN trained on 22,686 before-and-after photographs — achieving 85% rhino-plasty status classification accuracy with sensitivity 0.840 and specificity 0.826, equiva-lent to expert surgeons [28]. Topsakal et al. [26] used ML-based AutoGluon framework on synthetic 3D nasal models, achieving 82–88% accuracy in objective rhinoplasty out-come scoring—the first study to correlate visual appearance with quantitative facial measurements across simulated outcomes [26].

Large Language Models in Patient Counseling

Xie et al. [24] evaluated ChatGPT responses to nine rhinoplasty consultation questions from the American Society of Plastic Surgeons checklist, finding coherent, accessible answers but limited capacity for personalized guidance [24]. Capelleras et al. [23] used standardized postoperative questions from the Rhinobase database, demonstrating ChatGPT's potential to enhance patient education and alleviate emotional distress dur-ing recovery, while emphasizing that AI cannot substitute personalized clinical advice [23]. Durairaj et al. [22] conducted the most rigorous comparative evaluation, collecting responses from ChatGPT-3.5 and an expert rhinoplasty surgeon with over two decades of experience, rated by seven blinded expert surgeons. ChatGPT outperformed the phy-sician in accuracy, completeness, and overall quality across all metrics ($p < 0.001$) and was preferred in 80.95% of instances [22]. Aliyeva et al. [21] evaluated ChatGPT-4 us-ing ten standardized recovery questions rated by blinded ENT specialists, finding accu-racy scores of 90% (95% CI: 84.9–95.1) and clarity scores of 87% (95% CI: 82.8–91.2), but lower patient-centered communication performance of 77% (95% CI: 74.0–80.0) [21]. Lim et al. [25] investigated AI image generation tools for surgical education, doc-umenting the predominance of young, light-skinned female faces in generated imagery and raising concerns about demographic representation [25].

Postoperative Outcome Evaluation

Dorfman et al. [29] analyzed 100 female open rhinoplasty patients using Microsoft Az-ure Face API, finding an average post-surgical age reduction of 3.10 years versus virtu-ally no change from true age preoperatively, with a high correlation coefficient between actual and predicted preoperative age ($r = 0.91$) [29]. Parsaei et al. [27] applied Haystack AI software to Vectra 3D photographs of 40 rhinoplasty patients, demonstrating statis-tically significant increases in AI-rated attractiveness (+0.58, $p = 0.004$) and decreases in perceived age relative to true age (−1.62 years, $p = 0.021$) following surgery [27]. Complementing AI-based outcome assessment, Dehghani et al. [31] demonstrated in a randomized clinical trial that the lateral crural overlay technique produced significantly greater columella-labial angle changes than septocolumellar suture at six months postop-eratively ($p = 0.005$), providing objective photographic evidence that specific surgical technique selection directly and measurably influences nasal tip rotation outcomes [31]. Eldaly et al. [1] conducted a systematic review of simulation and AI in rhinoplasty across five databases, identifying ML approaches that learn individual surgical styles, deep learning models achieving high rhinoplasty status classification accuracy, and a DL model demonstrating that rhinoplasty makes patients appear younger [1]. Zhang et al. [32] evaluated CNN-estimated age reduction following facelift surgery in 50 patients, finding a positive correlation between neural network estimated age reduction (mean −4.3 years) and FACE-Q patient satisfaction scores [32]. Levites et al. [33] applied emo-tional AI to plastic surgery social media data, finding that "nose job" generated the greatest awareness of all plastic surgery search terms studied, and demonstrating AI's potential to provide insights into patient motivations [33].

Related Facial Plastic Surgery Applications

Seo et al. [34] applied AI-assisted landmark autodigitization to automatically identify 34 hard and soft tissue landmarks from CT images of cleft and non-cleft orthognathic surgery patients, enabling quantitative analysis of soft-to-hard tissue movement ratios [34]. Lu et al. [35] demonstrated that neural networks correctly gender-typed facial fem-inization surgery patients as female in only 54.5% of preoperative images, improving to 93.7% postoperatively, establishing a framework for AI-based objective outcome as-sessment [35]. Dusseldorp and Hadlock [36] applied ML algorithms to quantify im-provements in joy expression and reductions in negative emotion following smile reani-mation surgery, establishing methods directly applicable to facial plastic surgery out-come assessment more broadly [36]. Bukret [37] validated a novel AI-assisted risk as-sessment model for aesthetic surgery using ML, achieving 97.3% accuracy on the test sample, with BMI, age, and Caprini score identified as significant

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risk predictors [37]. Reyes et al. [38] conducted a systematic review of AI in facial plastic and reconstructive surgery, identifying computer vision and CNN-based models as the dominant method-ology for objective pre-to-postoperative comparison [38]. Spoer et al. [7] similarly re-viewed AI across plastic surgery subspecialties, finding that 43.2% of studies were in discovery phase and 27.3% in technical performance phase, with only one study demon-strating translation to clinical practice [7].

Table 1. Distribution of included studies by AI application domain.

Domain	*Number of Studies*	*Representative References*
Preoperative planning & simulation	*11*	*[11,12,13,14,15,16]*
Aesthetic analysis & attractiveness	*9*	*[17,18,19,20]*
LLM-based patient counseling	*6*	*[21,22,23,24,25]*
Intraoperative guidance & AR	*3*	*[4,10,12]*
Postoperative outcome evaluation	*10*	*[26,27,28,29]*

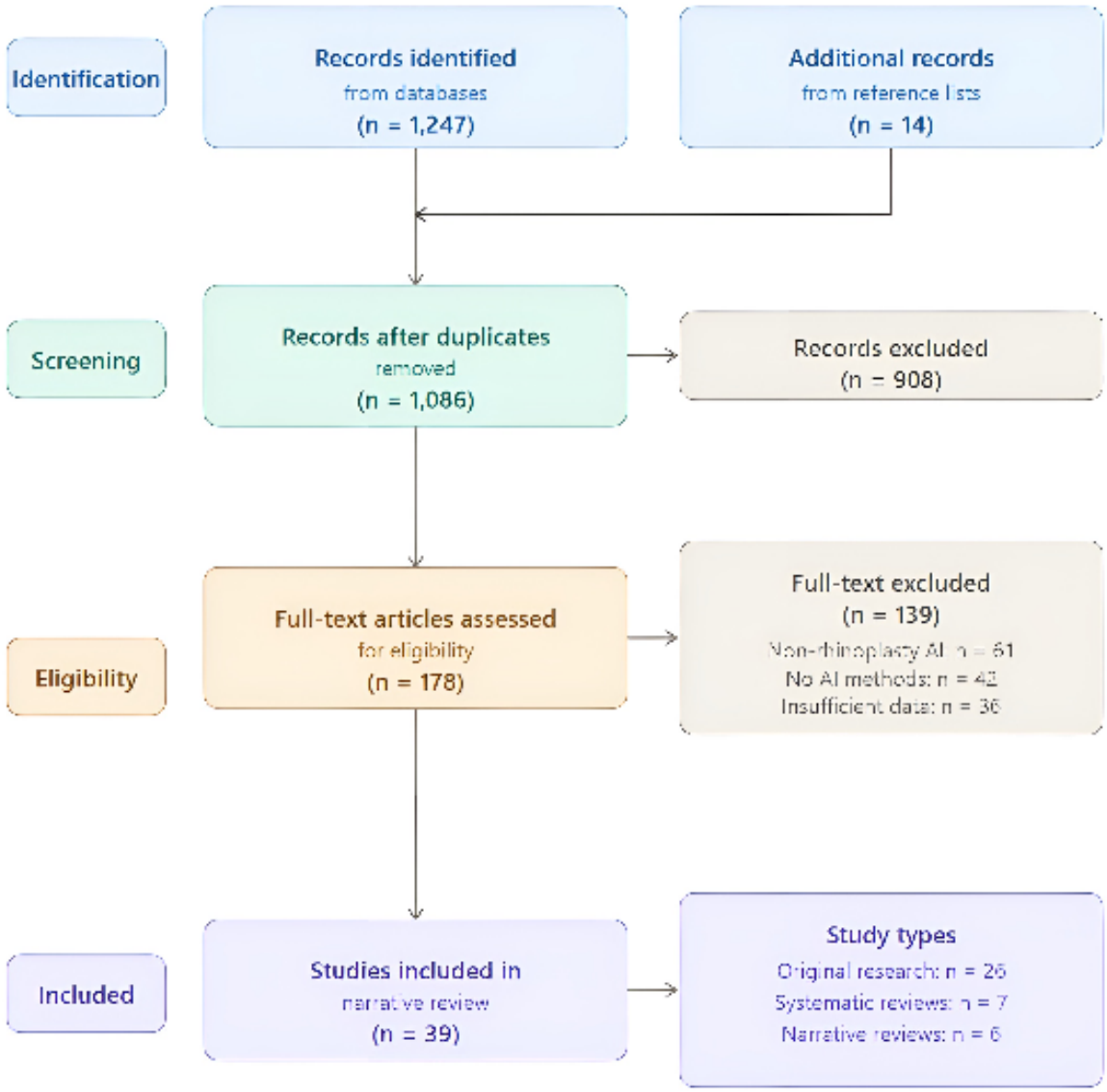


Figure 1. PRISMA flow diagram illustrating the study selection process.

Discussion

Preoperative Simulation: Promise and Limitations

The development of AI-driven preoperative simulation tools represents one of the most clinically accessible advances in this domain. The work of Li et al. [14] demonstrating automated 3D nasal design comparable to manual simulation [14], and Chinski et al. [15] showing that AI-generated simulations achieved specialist agreement rates ap-proaching those of the surgeon [15], suggests these tools are reaching clinically meaning-ful performance thresholds. However, as De Bernardis et al. [9] emphasized, AI cannot account for individual healing processes, tissue behavior, and long-term nasal remodel-ing [9]. This is a fundamental limitation: a simulation may be geometrically accurate yet clinically misleading if it fails to communicate the probabilistic and biologically variable nature of surgical outcomes. Subtle anatomical subunits—such as the soft triangle, where dermis lies in direct contact with dermis without intervening subcutaneous tissue—remain particularly vulnerable to unintended intraoperative injury and are difficult to incorporate into current simulation models [39].

Singh and Pearlman [2] documented that 63% of surveyed facial plastic surgeons al-ready used computer imaging in rhinoplasty consultations, with 92% performing the im-aging themselves [2]. AI-based automation of this process could expand access to simu-lation-assisted consultation and reduce the time burden, particularly for less experienced surgeons [14]. However, Lekakis et al. [39] demonstrated that patients with body dys-morphic disorder—who are significantly less satisfied after rhinoplasty—cannot be reliably identified without formal screening [39]. As AI simulations become more photo-realistic and persuasive, the risk of reinforcing unrealistic expectations in psychologically vulnerable patients increases, making BDD screening an ethical imperative alongside simulation deployment [9,39].

Aesthetic Quantification: Objectivity and Its Paradoxes

The use of ML to quantify aesthetic outcomes offers a theoretically more objective basis for evaluating rhinoplasty results than subjective surgeon or patient assessment. The finding by Štěpánek et al. [7,17] that nasolabial and nasofrontal angle enlargement sig-nificantly predicts attractiveness improvement [17,20]—corroborated by Bayar Muluk (2026) [3]—provides surgeons with ML-validated targets for aesthetic planning. The demonstration by Borsting et al. [28] that a CNN can classify rhinoplasty status as accu-rately as expert surgeons from images alone [28] highlights the extent to which nasal surgery creates detectable, consistent visual change. However, the objectivity of AI-based aesthetic assessment is itself a construct. Mahmood et al. [19] found that rhinoplasty shifted patients toward an above-average attractiveness phenotype defined partly by photographs of actresses [19]. Patcas et al. [18] found that AI attractiveness scores for control subjects were systematically lower than human panel ratings, suggesting model biases that may not align with diverse hu-man aesthetic judgments [18]. Lim et al. [25] documented the predominance of young, light-skinned female faces in AI-generated surgical imagery [25], while Cikita and Mas'ud [13] emphasized that most AI models lack culturally inclusive morphometric da-ta [13]. These findings collectively caution against treating AI aesthetic quantification as culturally neutral or universally valid.

Large Language Models: A Complex Landscape

The performance of LLMs in rhinoplasty-related counseling tasks warrants careful inter-pretation. Durairaj et al. [22] found that ChatGPT-3.5 outperformed an expert surgeon in blinded evaluations of counseling quality across most domains [22]—a finding that initially appears remarkable but must be contextualized. The evaluation measured per-formance on standardized, closed-ended questions where the LLM could draw on vast training data. Such conditions favor LLMs, which excel at synthesizing consistent, comprehensive text responses, over clinicians who may prioritize brevity and individual-ization in written responses. The consistent finding across Xie et al. [24], Capelleras et al. [23], and Aliyeva et al. [21] that LLMs perform well on accuracy and clarity but more modestly on patient-centered communication reflects a genuine limitation: LLMs cannot perform individualized clinical assessment, cannot examine the patient, and can-not integrate the contextual nuance that underlies truly patient-centered communication. These findings suggest that LLMs may serve a valuable role in standardized patient ed-ucation—answering common questions, providing general reassurance during recovery, and improving consistency of information delivery—while the relational and individu-alized dimensions of counseling remain the domain of the clinician [21,23].

Postoperative Outcome: Moving Toward Objectivity

The convergence of findings from Dorfman et al. [29], Parsaei et al. [27], and Zhang et al. [32] —showing that

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AI can consistently detect improvements in perceived youth and attractiveness following facial surgery, and that these AI estimates correlate with patient-reported satisfaction—establishes a methodological framework of significant clinical relevance. Objective AI-based outcome metrics could supplement or partially replace subjective surgeon assessments and patient-reported outcomes, improving stand-ardization of outcome evaluation across institutions and over time. Topsakal et al. [26] demonstrated that ML outcome scoring achieves 82–88% accuracy [26], while Levites et al. [33] showed that AI can extract meaningful signal from large unstructured social media datasets about patient motivations [33]—extending the scope of AI-assisted outcome research beyond the clinic. The importance of structured, multi-parameter out-come measurement is further underscored by Razmara et al. [40], who found that pa-tient satisfaction following genioplasty—a procedure frequently combined with rhino-plasty—was significantly influenced by the number of follow-up sessions ($p = 0.076$) and type of procedure performed, with advancement genioplasty yielding the highest long-term satisfaction; such findings highlight the complexity of patient-reported out-comes that AI-based tools must ultimately capture [40].

Ethical Considerations

Several ethical concerns recur throughout the reviewed literature. First, algorithmic bias arising from non-representative training data risks systematically disadvantaging patients from underrepresented demographic groups [10,13,25]. As Dumitrascu et al. [5] noted, restricted data diversity and opaque model architectures are among the most significant barriers to responsible AI adoption in aesthetic surgery [5]. Second, De Bernardis et al. [9] identified medico-legal risks from AI-generated simulations that may generate unre-alistic patient expectations, particularly in the context of social media-driven aesthetics [9]. Third, data privacy in the use of facial photographs for model training remains in-completely regulated, and patient consent frameworks for AI-based simulation and counseling tools are still evolving [10]. Fourth, as Rokhshad et al. [10] emphasized, sys-tematic ethical reflection on data protection, diversity, and transparency is as important as technical validation for responsible AI deployment in cosmetic surgery [10].

Current Limitations of the Evidence Base

The body of evidence reviewed carries important limitations. Most studies are retrospec-tive in design. Dataset sizes are frequently modest and derived from single institutions. Demographic representation in training datasets is often narrow. External validation on independent datasets is rarely performed. Standardized evaluation frameworks for AI in rhinoplasty do not exist [6,7,8]. As Spoer et al. [7] noted, the vast majority of AI re-search in plastic surgery remained in preclinical phases [7], and Bulfamante et al. [8] identified an inherent lack of accessible code sources as a barrier to replication and re-search advancement [8]. These limitations do not diminish the genuine promise of the technology but counsel against premature clinical adoption.

Conclusion

Artificial intelligence has entered rhinoplasty across a broad front, demonstrating mean-ingful capabilities in automated preoperative simulation [14,15], aesthetic analysis [17,26,28], patient counseling [21,22,23,24], intraoperative guidance [12], and postopera-tive outcome evaluation [27,29,35]. The most practically mature applications include LLM-based patient education and CNN-based outcome quantification, while fully inte-grated AI-guided surgical planning and intraoperative assistance remain in earlier stages [1,7]. Reported model accuracies of 82–97% across outcome scoring and attractiveness classification tasks [17,26,28] are encouraging, though they reflect controlled research conditions rather than validated real-world performance.

The evidence base, while growing, is characterized by predominantly retrospective stud-ies, methodological heterogeneity, limited demographic diversity, and absence of pro-spective clinical validation [6,7,8]. These limitations counsel against uncritical clinical adoption. Specifically, before AI tools in rhinoplasty are incorporated into routine prac-tice, they should demonstrate performance through prospective clinical validation, mul-ticenter external validation, regulatory approval, and clinical impact studies showing im-proved patient outcomes—not merely improved simulation or classification metrics [5,7,9]. AI in rhinoplasty is most responsibly understood not as a competitor to surgical exper-tise but as a powerful set of tools that, developed and deployed with appropriate over-sight, has the potential to make excellent rhinoplasty more accessible, reproducible, and objectively evaluable. Surgeons are encouraged to engage proactively in shaping AI de-velopment toward clinically meaningful questions while maintaining the human judg-ment, ethical responsibility, and individualized patient care that remain irreducible ele-ments of surgical practice [3,4,10].

Conflict of Interest

There is no conflict of interest to declare.

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