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Artificial Intelligence–assisted Risk Stratification in Aesthetic Surgery: A Prospective Observational Study

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Background: Enhancing patient safety and minimizing complications are critical objectives in aesthetic surgery. In 2021, the author developed and validated an artificial intelligence (AI)–assisted risk stratification model to predict complications and support clinical decision-making. This study aimed to evaluate the clinical impact of surgical risk stratification on patient outcomes.

Methods: A prospective observational study was conducted from January 2021 to May 2024 to assess 3347 patients, using an AI model. The patients were stratified into high-, moderate-, and low-risk groups and received tailored recommendations. A total of 74 patients proceeded with surgery, and their outcomes were analyzed. Statistical analyses included logistic regression and correlation tests ($P < 0.05$).

Results: Of the 3347 patients assessed, 18.55% were high-risk, 30.56% were moderate-risk, and 50.88% were low-risk patients. Among the 74 patients who underwent surgery, 7 (9.46%) developed 11 complications, with the high-risk group showing a relative risk of 6.73. Logistic regression confirmed that age and Caprini score were independent risk factors, whereas body mass index and smoking showed no statistical association with complications, likely because of effective preoperative risk mitigation, including weight optimization and smoking cessation protocols enforced by the AI model.

Conclusions: This study demonstrated that AI-assisted risk stratification effectively identifies risk factors in aesthetic surgery, enabling personalized preoperative recommendations to mitigate complications. AI can enhance patient safety and surgical outcomes by enabling systematic risk stratification. Integrating AI into surgical planning optimizes patient selection and supports its implementation in clinical decision-making. *(Plast Reconstr Surg Glob Open 2025;13:e6948; doi: 10.1097/GOX.0000000000006948; Published online 16 July 2025.)*

INTRODUCTION

Plastic surgery prioritizes safety and satisfaction and emphasizes preoperative risk assessment. Traditional clinical judgment may overlook complex risk profiles and increase the risk of developing complications. The American Society of Anesthesiologists (ASA) introduced the physical status classification system in 1941, establishing a standard for anesthetic risk assessment in preoperative patients.[1]

In 2011, the American Society of Plastic Surgeons task force expanded the safety guidelines and defined high-risk patients as those with a body mass index (BMI) greater than 35 kg/m², age older than 60 years, operative time longer than 6 hours, lipoaspirate volume greater than 5000 mL, or those undergoing combined procedures, particularly abdominoplasty with large-volume liposuction. Additionally, cardiopulmonary diseases such as obstructive sleep apnea are recognized as high-risk factors.[2]

Building on this, Rohrich et al (2018) updated the risk criteria as follows: BMI greater than 30 kg/m², operative time longer than 4 hours, lipoaspirate volume greater than 3 L, and combined procedures. They noted that outpatient plastic surgery studies rely on database queries and

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surveys, often excluding plastic surgery patients or failing to identify risk factors for complications.[3]

Traditional risk assessment models for plastic surgery have limitations in terms of sensitivity and usability. In 2014, Saldanha et al[4] introduced a scoring system that incorporated surgery duration, BMI, and ASA classification. However, its complexity and reliance on multiple parameters hinder its adoption. Human-based calculations struggle to integrate risk factors, reduce assessment sensitivity, and may potentially overlook complications.[4] Similarly, the Caprini score, a standard for predicting venous thromboembolism, does not account for other surgical complications, underscoring the need for a more holistic risk assessment tool.[5]

In 2021, Bukret[6] introduced an artificial intelligence (AI) risk assessment model, integrating BMI, age, Caprini score, and smoking habits and correlating them with a broad range of surgical complications. This evidence-based tool enhances the precision of patient-specific risk evaluation while reducing complexity.[7]

The model generates AI-driven recommendations and optimizes surgical planning and patient safety. By automating risk stratification, it streamlines decision-making and prevents complications while preserving individualized care.

This study evaluated the real-world utility of an AI-driven approach to plastic surgery, focusing on risk stratification, key factor identification, and clinical correlations to assess its impact on surgical safety and decision-making. The author hypothesized that the AI model would be a useful method for structured and systematic risk stratification and tailored recommendations in real-world settings to support surgical decision-making.

Takeaways

Question: How can artificial intelligence (AI) improve risk stratification and patient safety in aesthetic surgery?

Findings: This prospective study evaluated an AI model on 3347 aesthetic surgery patients, demonstrating its ability to classify risk and provide personalized recommendations. The model effectively stratified complication risk and reinforced preoperative interventions, such as weight optimization and smoking cessation, contributing to enhanced surgical planning.

Meaning: AI-assisted risk stratification can enhance patient safety by identifying high-risk individuals and guiding preventive measures to optimize aesthetic surgery outcomes.

MATERIALS AND METHODS

Study Design and Setting

This prospective observational study was conducted between January 2021 and May 2024, in a single plastic surgery practice in Buenos Aires, Argentina. This study aimed to evaluate the clinical utility of an AI risk assessment model for structured and systematic risk stratification and tailored recommendations for elective surgery to support surgical decision-making.

Participant Selection

Patients 18 years or older undergoing elective aesthetic surgery were included if they completed the AI-based preoperative assessment and agreed to follow its pre- and postoperative recommendations. Patients who had undergone reconstructive surgery were excluded from the study.

Exclusion Criteria

The following are the exclusion criteria:

- Age younger than 18 years.
- Severe allergic reactions to anesthesia (out of AI model scope).
- Cognitive impairment preventing informed consent.
- Pregnancy/lactation.
- Uncontrolled systemic diseases (eg, diabetes, cardiopulmonary diseases, and immunosuppressive disorders).
- Emergency surgery or incomplete clinical data.
- Noncompliance with medical recommendations.
- Enrollment in other clinical trials.

Follow-up Period

The follow-up period ranged from 2 to 41 months (mean, 15 mo), with monitoring of the complication rates and patient satisfaction.

Ethical Considerations

Given the anonymized data and solo practice settings, institutional review board approval was not required. Informed consent was obtained from all the participants in accordance with the Declaration of Helsinki.

Data Collection and Anonymization

Data were collected using a standard electronic medical record intake questionnaire that is routinely used in clinical practice. The AI model assessed all patients, including those seeking nonsurgical procedures (eg, injectables), ensuring comprehensive risk stratification. Moderate- and high-risk cases were identified to enhance surgical decision-making. Unique alphanumeric codes were used to replace the identifiable data to ensure strict anonymity. The anonymization process ensured data integrity, allowing for an accurate correlation between risk assessment and surgical outcomes.

AI Algorithm

The previously validated AI model uses a weighted sum method that integrates BMI, age, smoking status, and the Caprini score. It was trained using a support vector machine on 372 patients (80/20 split), achieving 97.3% accuracy.[6]

Risk Stratification and Recommendations

The following steps outline the process of risk stratification and personalized recommendations:

Input collection: Patients completed a detailed clinical form. (**See table, Supplemental Digital Content 1**, which displays the full list of evaluated clinical factors by the AestheticSafe model, **https://links.lww.com/PRSGO/E169**.)

Risk calculation: The AI model computed personalized risk scores using clinical data.

Risk groups: Low risk (score <1.2), moderate risk (score 1.2–1.4), and high risk (score ≥1.4).

Personalized recommendations: This model generates specific recommendations based on risk assessment, addressing various conditions (Fig. 1). (**See table, Supplemental Digital Content 2**, which displays the algorithm recommendations table, **https://links.lww.com/PRSGO/E170**.)

Outcome Measures

The primary outcome was the incidence of surgical and related complications within 45 days after surgery, including, but not limited to, hematoma, seroma, infection, and anesthesia-related complications. Data were collected through follow-up visits and patient self-reports.

Statistical Analysis

All statistical analyses were conducted using Python (Colab) software. Descriptive statistics were used to summarize the patient characteristics and complication rates. The Kruskal–Wallis *H* test was used to compare complication rates across nonparametric risk groups. The Pearson correlation coefficient was used to evaluate the association between risk factors and AI-predicted risk scores.

The relative risk and odds ratios (ORs) with 95% confidence intervals (CI) were calculated for each risk group. A *P* value of less than 0.05 was considered statistically significant in all tests.

To account for variability in follow-up durations (2–41 mo), statistical modeling was designed to focus on the first 6 postoperative weeks, as this was the predefined period for complication assessment. Sensitivity analyses were planned to compare the full dataset (n = 74) with a subset of patients having 6 weeks or less of follow-up, ensuring that statistical comparisons were not influenced by differences in follow-up duration.

Addressing Bias and Confounding Variables

To minimize potential bias, strict anonymization protocols and standardized data collection methods were implemented for all participants. This study aimed to reduce confounding variables by ensuring a uniform preoperative assessment and surgical protocols. Given the structured methodology, sensitivity analyses were deemed unnecessary, as no major confounders were identified.

RESULTS

Patient Population and Data Collection

A total of 3347 patients were assessed using the AI risk assessment model, comprising 2886 women (86.22%) and 461 men (13.77%). Patients were categorized into 3 risk groups: high risk (18.55%, n = 621), moderate risk (30.56%, n = 1023), and low risk (50.88%, n = 1703) (Fig. 2). Among the 74 surgical candidates, the distribution was high risk, 4.05% (n = 3); moderate risk, 21.62% (n=16); and low risk, 74.32% (n = 55).

Of the 3347 patients surveyed, 74 underwent surgery based on clinical suitability and patient

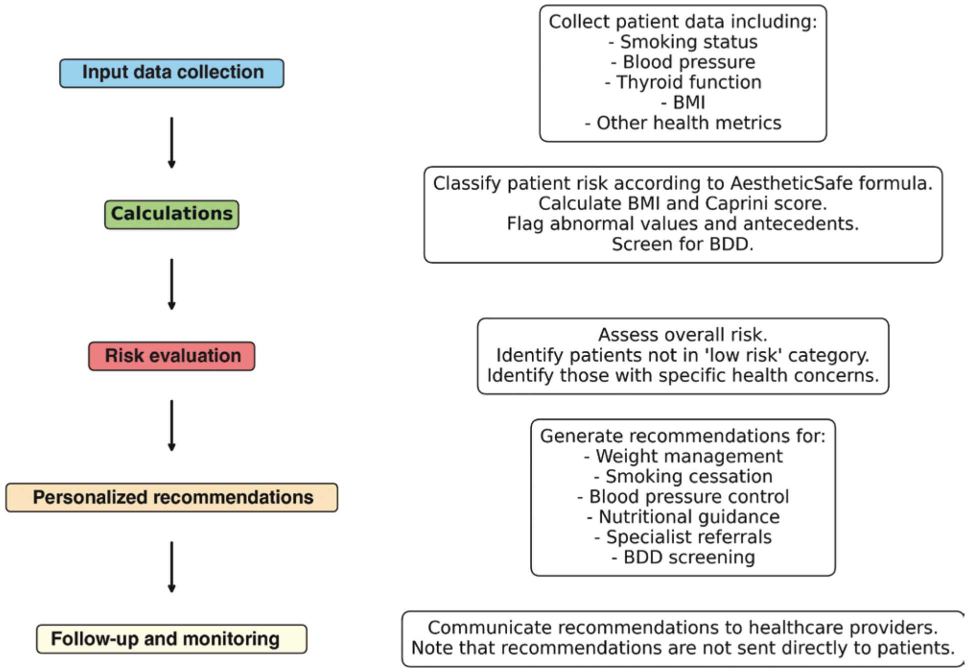

Fig. 1. Flowchart of the AI model's recommendation system for plastic surgery risk assessment.

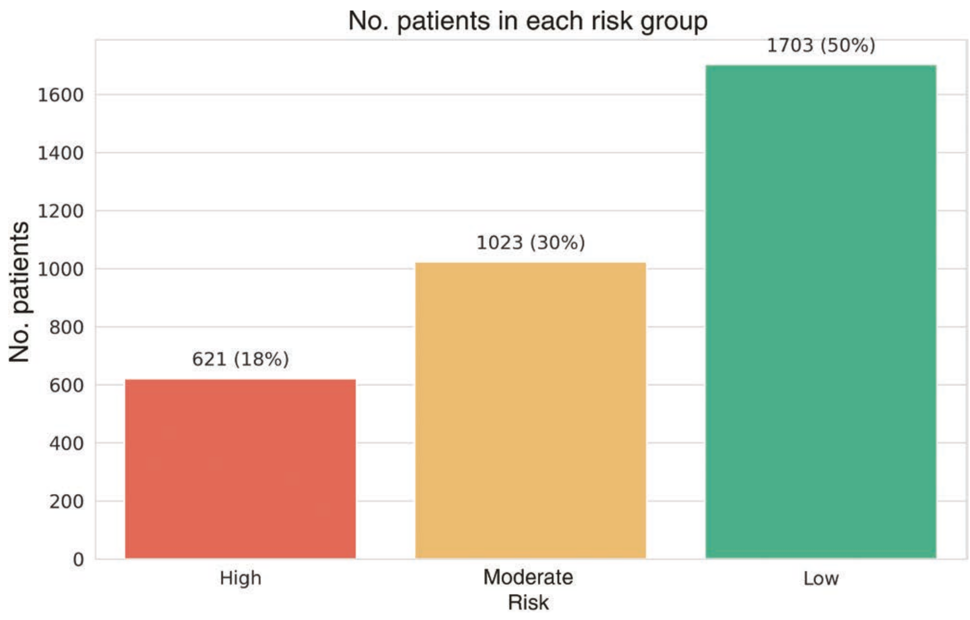

Fig. 2. Number and percentage of patients per risk group.

Table 1. Summary of Surgical Outcomes and Complication Rates

Metric	Value	Percentage
Total treated patients	74	2.21
Total complications	11	14.86
No. patients with complications	7	9.46
Average complications per patient	0.15	14.86

preference. The remaining patients were excluded because of high-risk classification, surgical unsuitability, or personal preference for nonsurgical management, aligning with real-world clinical workflows. The follow-up period ranged from 2 to 41 months (mean 15 mo).

Complication Rates and Risk Distribution

Of the 74 surgical patients, 11 (14.86%) had complications, affecting 7 patients (9.46%). One patient experienced 3 complications, and 2 patients experienced 2 complications each (Table 1). Each complication and its corresponding case are detailed in Table 2 and Supplemental Digital Content 3, and are summarized as follows (**See table, Supplemental Digital Content 3**, which displays detailed case descriptions, **https://links.lww.com/PRSGO/E171**.):

- Severe sepsis and hemorrhage: 1 patient (case 1).
- Hematoma: 2 cases (cases 2 and 5).
- Seroma: 4 cases (cases 2, 3, 4, and 7).
- Wound dehiscence: 1 case (case 3).
- Autoimmune syndrome induced by adjuvants (ASIA syndrome): 1 case (case 3).
- Infection: 1 case (case 6).

The complication rates were 4.05% (high risk), 0.0% (moderate risk), and 10.81% (low risk), consistent with the data presented in Table 3.

STATISTICAL ANALYSIS

The distribution of complications was as follows: 3 complications (27.27%) occurred in the high-risk group, none (0%) in the moderate-risk group, and 8 complications (72.73%) in the low-risk group. The complication percentage of the total number of treated patients (n = 74) in each risk group was 4.05%, 0.0%, and 10.81% in the high-, moderate-, and low-risk groups, respectively. The Kruskal–Wallis H test was used to compare the complication rates among the 3 groups. The test statistic was 3346.0, and the P value was less than 0.001, indicating statistically significant differences between the groups. The high-risk group had a relative risk of 6.73, whereas the moderate-risk group had a relative risk of 0, compared with the low-risk group, which served as the reference with a relative risk of 1 (Table 3).

ORs for Risk Factors

ORs were calculated as part of an exploratory analysis to assess the association between risk factors and complications (Table 4):

- Age: OR = 1.5 (95% CI, $P = 0.0100$).
- BMI: OR = 1.0 (95% CI, $P = 0.8067$).
- Caprini score: OR = 3.0 (95% CI, $P = 0.2414$).
- Smoking habit: OR = 0.0 (95% CI, $P = 0.5079$).

Although these findings provide insights into the potential risk factors, the small sample size limits their statistical significance.

Correlation Analysis

Correlation analysis demonstrated significant positive relationships between the clinical risk factors and the algorithm-generated risk scores (Fig. 3):

- BMI: $r = 0.999$, $P < 0.001$.
- Caprini score: $r = 0.999$, $P < 0.001$.
- Age: $r = 0.999$, $P < 0.001$.

Table 2. Summary of Risk Group Classification, Surgery Types, Risk Factors, and Complications per Patient

Risk	Main Surgery of Interest	Age, y	BMI, kg/m²	Caprini Score	Smoking Habit	Compli-cations	Hema-toma	Seroma	Necrosis	Infection	Dehiscence	Asia Syndrome
High	Abdominoplasty (any tummy tuck including liposuction)	42	27.2	6	0	2	1	1	0	0	0	0
High	Face lift	72	24.7	5	0	1	1	0	0	0	0	0
Low	Buttock augmentation with implants	33	19.4	2	0	3	0	1	0	0	1	1
Low	Liposuction (any method)	48	23.1	3	0	1	0	1	0	0	0	0
Low	Rhinoplasty (nose surgery)	21	17.6	3	1	1	0	0	0	1	0	0
Low	Buttock augmentation with fat	41	24.2	3	0	1	0	0	0	1	0	0
Low	Buttock augmentation with implants	26	17.0	2	0	1	0	1	0	0	0	0

Table 3. Summary of Risk Groups, Complication Rates, and Relative Risk

Risk	Operated On	Complications	Total Patients	Within-group Complication, %	Relative Risk	Total Complication, %
High	3	3	621	100	6.73	4.05
Moderate	16	0	1023	0.0	0.0	0.0
Low	55	8	1703	14.55	1	10.81

Table 4. Summary of ORs, Demographics, and Descriptive Statistics for Risk Factors

Risk Factor	Mean ± SD	Minimum	Maximum	OR	*P*
Age, y	34.00 ± 11.85	18.0	78.0	1.5	0.01
BMI, kg/m²	24.41 ± 4.34	15.8	45.8	1.0	0.81
Caprini score	2.78 ± 1.20	2.0	20.0	3.0	0.24
Smoking habit	N/A	N/A	N/A	0.0	0.51

N/A, not available.

- Smoking habits: $r = 0.933$, $P = 0.015$.
- Male gender: $r = 0.869$, $P = 0.006$.
- Female gender: negative correlation, $r = -0.869$, $P = 0.006$.

Assessment Outcomes and Follow-up Variability

Table 5 provides an example of the assessment results and recommendations for a high-risk patient. The follow-up period ranged from 2 to 41 months (mean 15 mo). Sensitivity analyses confirmed that all complications occurred within 6 weeks postoperatively and that rates were consistent between the full dataset (n = 74) and those with 6 weeks or less of follow-up. Table 6 presents the low-risk group as the baseline. The high-risk group had a relative risk of 6.73, whereas the moderate-risk group had a relative risk of 0. No new complications occurred in the patients who were followed up for more than 6 weeks.

DISCUSSION

This study evaluated the utility of the Bukret[6] AI-based risk assessment model. The model translates risk assessments into personalized recommendations and provides decision support. By identifying high- and moderate-risk patients, AI-driven recommendations mitigate risks, avoid unnecessary procedures, and optimize surgical planning.[6]

High-risk patients underwent a comprehensive evaluation. In several cases, surgery was avoided when the risks outweighed the benefits, thus underscoring the role of the model in preventing complications in unsuitable candidates. It aligns with the surgeons' clinical judgment, minimizing preventable errors such as data omissions and misclassifications. Future studies should include diverse patient populations to strengthen the model's applicability.

Findings showed significant correlations between high-risk scores and surgical complications such as hematoma, infection, and seroma, consistent with prior studies.[6–10] Smoking was a major risk factor, consistent with the findings of Pluvy et al[11] and Kaoutzanis et al.[12,13] Age and BMI were also correlated with higher complication rates, reinforcing the findings of Gupta et al.[7,8]

A sensitivity analysis confirmed the robustness of the model. Despite variations in the follow-up duration, the complication rates were consistent across the datasets. The high-risk group had a relative risk of 6.73 compared with the low-risk group, whereas the moderate-risk group had a relative risk of 0, demonstrating the benefits of proactive stratification. These findings are consistent with those of the previous validation studies.[6]

The low-risk group served as a reference rather than a strict control, limiting direct comparisons. The AI model was designed to predict common complications (eg, deep vein thrombosis, infections), whereas rare

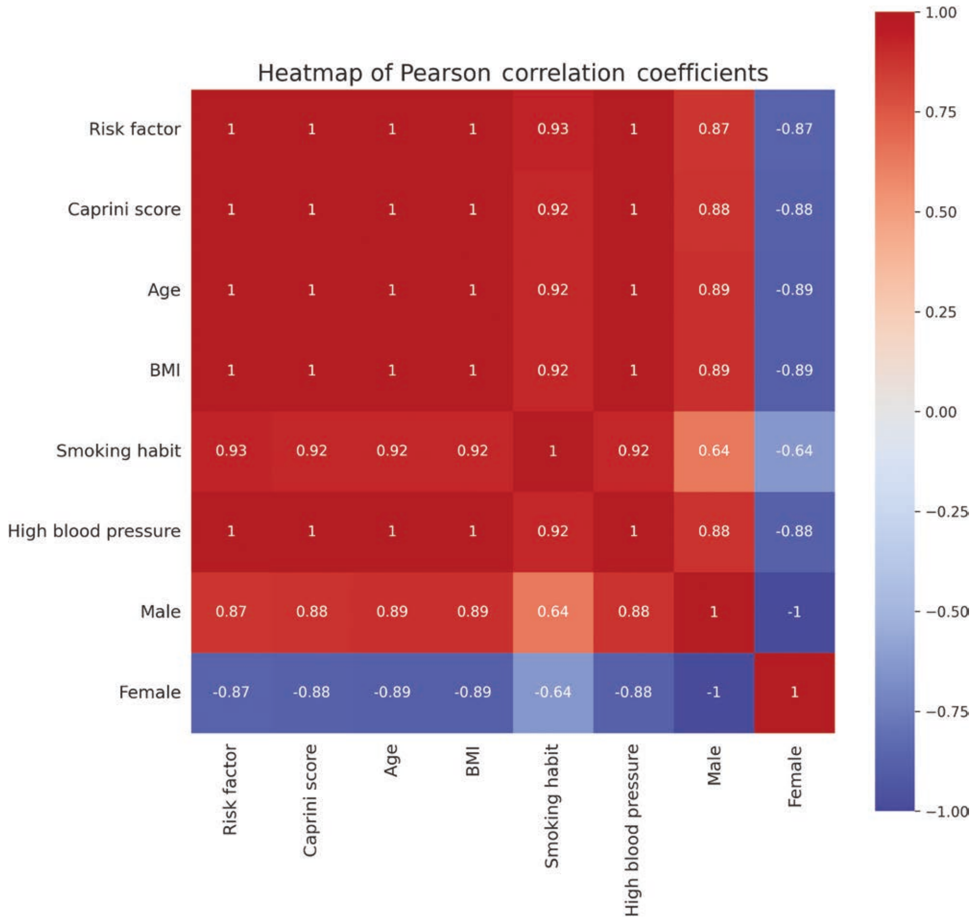

Fig. 3. Heatmap of correlation analysis results for risk factors.

Table 5. Example of Assessment Results and Recommendations

Assessment Results	Details
Clinical data	
Age, y	67
High blood pressure	Yes
Thyroid	Hypothyroidism
Alcohol consumption	Yes, less than 2 L/wk
Hereditary diseases	Yes
Calculated values	
Risk	High
BMI, kg/m^2	26.54
Caprini score	8
Recommendations	
Recommended weight	174.3 pounds
Monitor BP daily	Take notes to the cardiologist
Consult with endocrinologist	Consult with endocrinologist
Request ergometry and eco-Doppler of lower limbs	Request ergometry and eco-Doppler of lower limbs

BP, blood pressure.

events such as ASIA syndrome require larger datasets. Despite this, its predictive value remains relevant, as it stratifies risk using patient-specific data and supports surgical decision-making. The AI model enhances decision-making by integrating BMI, age, Caprini scores, and smoking habits into risk assessments and emits recommendations accordingly.

This aligns with prior research on multivariate risk prediction.[14,15] The Bukret[6] AI model achieved a 97.3% accuracy.

Despite not evaluating long-term satisfaction, the model's ability to reduce complications at a minimal cost highlights its clinical value. Future research should explore patient-centered outcomes and economic impacts.

The complication patterns confirmed the role of the model in surgical decision-making. The high-risk group had a relative risk of 6.73, indicating a greater likelihood of complications, whereas no complications in the moderate-risk group suggests effective perioperative management. However, severe complications in the low-risk group (eg, ASIA syndrome and propofol-related sepsis) highlight the need for larger datasets to address rare events better.

The AI model's recommendations, including smoking cessation and weight optimization, align with patient-centered care. This approach prepares patients for surgery and reduces early postoperative complications (≤6 wk), as shown by the sensitivity analysis. By systematically assessing multiple risk factors, the AI model addresses clinical challenges, improves decision-making, and enhances surgical outcomes by refining risk stratification and personalized care.

Table 6. Risk Group Classification With Relative Risks and Follow-up Complication Analysis

Risk Group	N (Patients)	Complications, n	Complication Rate, %	Relative Risk	Follow-up Observations
High-risk	621	3	4.05	6.73	Complications occurred within ≤6 wk only
Moderate-risk	1023	0	0.00	0.00	No complications observed
Low-risk	1703	8	10.81	Comparison group	Complications occurred within ≤6 wk only
Follow-up ≤6 wk	74	7	9.5	N/A	All complications observed in this period
Follow-up >6 wk	74	0	0.00	N/A	No new complications observed

N/A, not available.

The small sample size (n = 74) limits generalizability but reflects real-world decision-making rather than statistical constraints. This study assessed clinical applicability rather than model validation, making the sample size appropriate for elective surgery. ORs were explored, but were limited by the sample size. Notably, BMI and smoking status showed no significant association with complications, reflecting the preventive impact of AI-driven risk-reduction strategies, such as weight optimization and smoking cessation. These findings support the role of AI in optimizing surgical decision-making. Subgroup analyses were not feasible because of the limited sample size. However, future studies with larger datasets will refine the predictive accuracy, compare AI-assisted decision-making with standard clinical practice, and incorporate subgroup analyses for more granular risk assessment.[16]

The relative risk of 6.73 in the high-risk group confirms a higher likelihood of complications, consistent with the previous findings.[6] In contrast, the low-risk group experienced 8 complications (10.81%), all of which were minor and required no intervention.

The higher complication rate in the low-risk group may be attributed to sample size imbalances and the occurrence of rare and unpredictable complications. Notably, severe complications, such as ASIA syndrome and propofol-related sepsis, were observed in the low-risk group despite the absence of baseline risk factors. These rare events reflect the statistical limitations of low-frequency complications and reinforce the need for larger datasets.

In contrast, the moderate-risk group had a relative risk of 0, suggesting that effective surgical planning and perioperative management contributed to favorable outcomes. The lower complication rate in this group may also be due to the small sample size and tailored perioperative strategies applied. These findings reinforce the clinical value of AI-driven risk stratification and demonstrate its potential to enhance surgical safety and optimize patient selection.

This study confirmed the utility of the AI model in identifying high-risk patients and guiding safer decisions. By providing tailored recommendations, the model enables the proactive reduction of complications. However, further refinement in predictive accuracy remains crucial.

To the best of our knowledge, this AI-driven system is the first to introduce a novel approach to preoperative planning. By integrating comprehensive patient data, it provides specific recommendations for weight management, smoking cessation, blood pressure monitoring, and specialist referrals.

In elective plastic surgery, AI-driven models enable proactive risk management by addressing the modifiable risk factors. Engaging patients fosters control, enhances communication, and improves long-term outcomes. Reducing complications reduces costs and reinforces safety concerns. By involving patients in risk management, the model builds trust and appreciation for treatment complexity, contributing to better satisfaction and adherence, which are critical for optimal results.[13,17–24]

This study also highlighted the transparent logic of the AI model, which serves as a positive example of AI integration in surgery. This aligns with healthcare guidelines advocating explainable and interpretable models to ensure fair decision-making.[22,25]

The AI risk stratification model used in this study was previously validated by the authors, achieving 97.3% predictive accuracy. Developed using the best available evidence at the time of its 2021 publication, this study builds on that foundation, demonstrating its real-world clinical application in risk stratification and complication reduction.[6]

Although a randomized controlled trial with a control arm would further validate these findings, this prospective study is a critical step toward clinical integration. Future research should focus on multicenter randomized controlled trials to evaluate model efficacy and broaden applicability.[6]

LIMITATIONS AND FUTURE DIRECTIONS

Despite these advantages, the present study has several limitations. The small sample size and prospective design may have affected the generalizability of the results. Larger multicenter studies are needed to confirm these findings and to evaluate their performance across diverse clinical settings.

Additionally, the lack of a control group prevents a direct comparison with traditional methods. Future research should include a control arm for a clearer assessment of model effectiveness.

Convenience sampling may introduce a selection bias, which limits generalizability. Although practical for early-stage research, this approach requires randomized sampling in future studies to improve representativeness and minimize potential biases in patient selection.

The use of AI in plastic surgery raises concerns regarding bias, particularly with respect to race and sex. This study leveraged Argentina's diverse population, predominantly multiracial, mestizo, indigenous, and European. None of the patients were excluded based on race, ethnicity, or sex, and international patients showed enhanced heterogeneity.

To ensure equity, broad representation and universally recognized clinical factors were prioritized. This approach aligns with ethical guidelines for algorithmic decision-making, minimizing biases and ensuring fairness.[26]

Although diverse, the sample lacked explicit racial data and included only a limited bias analysis. Future research should incorporate demographic metrics to improve equity assessment and evaluate the impact of the AI model on broader surgical outcomes, including patient satisfaction, long-term aesthetics, healthcare costs, and the integration of body dysmorphic disorder screening and management for body dysmorphic disorder-risk patients, which is essential for addressing both psychological and physical needs. However, these aspects were beyond the scope of this study.[27]

CONCLUSIONS

This study demonstrated that AI-assisted risk stratification can identify risk factors for aesthetic surgery, enabling personalized preoperative recommendations to mitigate complications. AI can enhance patient safety and surgical outcomes by enabling systematic risk stratification. Integrating AI into surgical planning optimizes patient selection and supports its implementation in clinical decision-making.

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DISCLOSURES

Dr. Bukret is the developer of the AI risk assessment model discussed in this study and the founder and CEO of AIRA10 Medical LLC.

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