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INVITED REVIEW

Artificial intelligence in preoperative assessment and optimization: a narrative review

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ABSTRACT

Background: Preoperative assessment and optimization are pivotal for complex surgical patients, yet traditional scores and clinician-driven workflows may miss subtle risk interactions and modifiable factors. Artificial intelligence (AI), especially machine learning (ML), can leverage large-scale electronic health record (EHR) data to improve risk stratification and support targeted optimization strategies.

Methods: We conducted a narrative review focusing on practical, clinically actionable AI applications in preoperative assessment and optimization, emphasizing recent advances and implementation considerations for high-risk surgical patients.

Results: ML-based preoperative risk models can outperform conventional calculators, exemplified by a gradient-boosted decision-tree model trained on >1.4 million surgical cases that achieved an AUROC of 0.95 for 30-day mortality and exceeded NSQIP performance, with prospective real-world deployment. Automated frailty phenotyping from structured preoperative EHR data (demographics, ASA/acuity, ICD-10/CCS diagnoses, and routine labs) has also been externally validated in older adults and shows strong stepwise associations with adverse outcomes. AI additionally supports preoperative optimization by identifying actionable targets such as anemia risk (supporting early iron/EPO pathways), penicillin allergy delabeling opportunities, and improved detection of risky alcohol use via natural language processing of clinical notes. Successful clinical impact depends on workflow integration, interpretability, and attention to privacy, bias, regulation, and prospective evidence.

Conclusions: AI-enabled preoperative assessment can enhance identification of high-risk patients and systematically surface modifiable factors for optimization, with early evidence of improved predictive performance and feasible integration into point-of-care workflows. Future work should prioritize robust external validation across diverse populations, implementation studies demonstrating patient-centered benefit, and governance frameworks ensuring safety, fairness, and clinician trust.

Keywords: Artificial intelligence, management, optimization, preoperative assessment, prediction

Introduction

Preoperative assessment is a critical step in managing patients before major surgery, especially for complex surgical patients with multiple comorbidities or high-risk factors. Such complicated patients often face elevated risks of postoperative complications, prolonged hospital stays, or intensive care unit (ICU) admissions. Traditional preoperative evaluation relies on clinical judgment, risk scores (like ASA classification or NSQIP calculators), and multidisciplinary optimization (e.g., controlling chronic diseases, nutritional support, prehabilitation). In recent years, artificial intelligence (AI), particularly machine learning (ML) algorithms, has emerged as a promising tool to enhance preoperative risk stratification and patient optimization. By analyzing large volumes of health data, AI can uncover complex patterns not easily accessible to clinicians, potentially improving prediction of adverse outcomes and guiding tailored interventions.

This narrative review examines the role of AI in the preoperative assessment and optimization

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of high-risk surgical patients, aimes to highlight recent advances within the last 7 years, practical applications, and future directions. We focus on how AI-driven approaches may augment the preoperative clinic functions in identifying patient risk profiles, recommending optimization strategies, and ultimately improving surgical and operational outcomes.

Traditional challenges in identifying high-risk preoperative assessment

Complex surgical patients (such as elderly, frail and individuals with significant comorbid conditions) pose challenges in preoperative evaluation. These patients are more likely to suffer from complications like cardiac, respiratory events, delirium, or infections after surgery. Conventional risk assessment tools exist, for example, the ASA score, American College of Surgeons NSQIP risk calculator and various organ-specific risk indices, but they have limitations in accuracy for individual patients. They often use a limited number of variables and may not capture subtle interactions between patient factors. Moreover, identifying all modifiable risk factors (including unoptimized medical conditions and factors like substance use) can be time-consuming.

Preoperative optimization clinics have been established in many centers to address these issues, providing comprehensive assessment and interventions before surgery (e.g., anemia correction, smoking cessation, medication adjustments). These clinics have shown improved surgical outcomes by optimizing patients' conditions, reducing unnecessary tests, and minimizing last-minute cancellations (1). However, they require significant resources and rely on clinicians to accurately identify high-risk patients and intervention targets. This is where AI can contribute, by automating and refining risk detection and ensuring that no important detail is overlooked in complex patients.

AI for preoperative risk stratification

One of the more advanced applications of AI in perioperative medicine is predictive modeling for surgical risk. Machine learning algorithms can analyze extensive electronic health record (EHR) data to predict which patients are at high risk for adverse postoperative outcomes. These models may often outperform traditional risk prediction tools in accuracy. For example, Mahajan et al. (2) developed a preoperative ML model using gradient-boosted decision trees on data from over 1.4 million surgical cases. This model achieved an area under the ROC curve (AUROC) of 0.95 for 30-day mortality prediction and significantly outperformed the standard NSQIP surgical risk calculator (AUROC margin of 0.048) in identifying high-risk patients (2,3) using exclusively preoperative data. Notably, the ML model used only preoperative variables readily available in the EHR and was validated prospectively in clinical practice, suggesting it could integrate into real-world preoperative workflows to flag patients at risk. The authors concluded that such an AI tool may allow targeted perioperative interventions and resource allocation (e.g., ICU bed planning) to those who need it most (2). Similarly, an earlier study by Corey et al. (4) termed "Pythia" demonstrated that ML models could automatically curate EHR data and identify high-risk surgical patients, laying groundwork for subsequent AI risk predictors (4,5).

Cardiac & respiratory risk prediction

Specific risk predictions have also been enhanced through AI. Cardiac complications and pulmonary complications are two major concerns in high-risk patients. Modern ML models can incorporate granular patient data to predict these events more precisely than older scoring systems. For instance, researchers have applied ML to forecast postoperative major cardiac events (e.g. myocardial infarction) or cerebrovascular events, as part of composite risk modeling (2). For postoperative pulmonary complications (PPCs), numerous AI-driven models have been developed in recent years. These include models for general surgery patients and specialty-specific ones (such as for lung surgery) that use features like patient demographics, lung function, imaging results, and even intraoperative data to predict risks of pneumonia, respiratory failure, or need for ventilation. Many show high accuracy in identifying patients likely to develop PPCs, although some still require external validation.

Shelley et al. (6) note that while machine learning can produce powerful risk prediction models, it is crucial to choose appropriate endpoints and timing, predicting the right complication at a time when an intervention is possible, to make these models clinically useful (6). In practice, an AI model that flags a patient as high-risk for, say, respiratory failure could prompt preoperative pulmonary optimization (like inspiratory muscle training, bronchodilator therapy) or a decision to postoperatively monitor in ICU, thereby preventing or better managing the complication.

Frailty assessment

Another particularly important domain for risk stratification in complex patients is frailty. Frailty, often defined as an age-related decline in physiological reserves, is a strong predictor of poor surgical outcomes (e.g., mortality, delirium, loss of independence) in older adults. Traditional frailty assessments (like questionnaires or walking tests) can be subjective or time-consuming. AI offers a way to quantify frailty from routine data. Bai et al. (7) externally validated an AI-based preoperative frailty index derived from EHR data on over 150,000 surgical patients ≥65 years old. They used structured preoperative EHR data from the months before surgery, including demographics (e.g., age/sex), clinical acuity/history variables (e.g., ASA class, cancer history), and diagnosis information from ICD-10 codes grouped into CCS categories. They also included commonly available pre-op laboratory measurements (e.g., hemoglobin/hematocrit and related routine biochemistry). Patients classified in the highest frailty tier by the AI had dramatically higher odds of 30-day mortality (over 4-fold increase), longer hospital stays, and greater chances of discharge to nursing facilities compared to the least frail, confirming a strong, stepwise association between the AI frailty score and outcomes (7). Interestingly, this AI frailty index, which compiles dozens of deficit variables from the health record, performed as well as or better than procedure-specific frailty models, suggesting a generalizable tool. This kind of automated frailty assessment could alert clinicians to an at-risk elderly patient during preoperative clinic visits, prompting geriatric co-management or prehabilitation referrals. Incorporating frailty via AI thus refines risk stratification beyond what age and comorbidities alone convey.

Overall, machine-learning risk models have shown impressive capability in predicting a range of postoperative adverse events, from mortality to major complications. In fact, recent narrative analyses assert that ML algorithms are "superior to traditional models for predicting postoperative anemia, opioid dependence, diabetes complications, and mortality risks," thereby providing more precise risk stratifications which may elevate perioperative resource optimization plans (1,8). These algorithms can take into account complex interactions of variables (laboratory tests, vital trends, comorbid conditions, medications, etc.) that static risk scores cannot, and lead to more individualized risk profiles. The improved accuracy means fewer high-risk patients "fly under the radar" and fewer low-risk patients are subjected to unnecessary costly interventions, a better alignment of perioperative resources with patient needs. Importantly, many ML models now also incorporate techniques for interpretability (such as SHAP - Shapley Additive exPlanations (SHAP) is a model-agnostic interpretability framework that enables the explanation of predictions from any machine learning model, including complex "black-box" models such as neural networks. values or other explainable AI methods) to identify which factors are driving a given patient's risk score. This is critical for clinician acceptance: for example, AI might reveal that a patient's poorly controlled COPD, low albumin, and high ASA status are the top contributors to predicted risk, which aligns with clinical intuition and directs what needs to be optimized.

AI applications in preoperative anemia

Preoperative anemia is highly prevalent among surgical patients and is consistently associated with increased rates of perioperative transfusion, postoperative complications, prolonged hospital stay, and mortality. Artificial intelligence–based models have recently been developed to improve the identification of patients at risk for significant postoperative anemia or transfusion requirements, enabling earlier and more targeted preoperative interventions. Kolin et al. developed machine learning predictive models for postoperative anemia and blood transfusion in patients undergoing orthopedic surgery, using routinely available clinical variables such as age, sex, baseline hemoglobin concentration, and comorbidities. Their models demonstrated strong discriminative performance, with area under the receiver operating characteristic curves ranging from 0.88 to 0.90 for both postoperative anemia and transfusion outcomes (9). Importantly, the identification of patients with a predicted probability greater than 5% for severe postoperative anemia allowed clinicians to individualize preoperative management strategies. High-risk patients could be directed toward iron supplementation, erythropoietin therapy, or proactive blood cross-matching, whereas patients classified as low risk could safely avoid unnecessary laboratory testing or iron treatment. Beyond single-outcome prediction, AI-driven decision support systems are increasingly capable of integrating longitudinal laboratory trends and patient-level clinical data to recommend standardized anemia optimization pathways within preoperative clinics (1). This approach facilitates early detection and treatment of anemia, a critical step given that untreated preoperative anemia substantially increases exposure to allogeneic blood transfusion and its associated risks.

AI application in medication management

It represents another important domain of preoperative optimization where AI has demonstrated significant potential. A particularly illustrative example is the problem of inaccurate penicillin allergy labeling. A substantial proportion of surgical patients carry a documented penicillin allergy, which frequently leads to the use of second-line perioperative antibiotic prophylaxis, such as vancomycin or clindamycin, instead of first-line beta-lactams like cefazolin. This practice has been associated with higher rates of surgical site infections and antimicrobial resistance. However, many penicillin allergy labels are outdated, imprecise, or reflect non-allergic adverse reactions rather than true immunoglobulin E–mediated hypersensitivity (10). Artificial intelligence can assist in identifying patients suitable for allergy reassessment or delabeling. Jiang et al. applied a machine learning algorithm to neurosurgical inpatients and demonstrated that approximately 22% of recorded penicillin allergies were inconsistent with true allergy criteria. Their model accurately differentiated allergy from intolerance with a reported accuracy of 98%, effectively flagging patients eligible for penicillin allergy testing and potential delabeling (11,12). When integrated into the preoperative workflow, such AI systems could automatically

AI applications in preoperative patient optimization (Table 1).

Beyond risk prediction, AI is increasingly being used to guide and enhance preoperative optimization strategies, that is, the process of improving a patient's condition prior to surgery. Once high-risk patients are identified, the next step is to mitigate those risks. AI tools can assist in several domains.

a) Screen patient histories and prompt clinicians with alerts suggesting allergy consultation. This would allow a greater proportion of patients to receive optimal perioperative antibiotics, thereby reducing infection risk and improving antimicrobial stewardship. This example highlights how AI can systematically interrogate complex electronic health records to uncover optimization opportunities that might otherwise be overlooked in routine clinical practice.

b) Postoperative Analgesia - Artificial intelligence has also been widely applied to the prediction and

Table 1. Representative AI applications in preoperative assessment and optimization

Study / domain	Population / setting	Data inputs (preop unless stated)	Model / approach	Outcome(s)	Performance / key result	Validation / implementation	Preop clinic "actionability"
Mahajan et al – global risk stratification	>1.4M surgical cases	"Only preoperative variables readily available in the EHR"	Gradient-boosted decision trees	30-day mortality	AUROC **0.95**; outperformed NSQIP (ΔAUROC **0.048**)	Prospective, point-of-care deployment	Earlier flagging for ICU planning, monitoring, specialty consults
Corey et al ("Pythia") – automated risk identification	Surgical patients (EHR-curated)	Automatically curated EHR features	ML risk models ("Pythia")	High-risk patient identification	Foundational demonstration of automated EHR curation for risk prediction	Validated models; informs later tools	Automated preop triage; reduces manual data extraction burden
Bai et al – frailty phenotyping	≥65 years; >150k surgical patients	Demographics; ASA/acuity & history (e.g., cancer); ICD-10→CCS; routine labs (Hb/Ht, biochem)	AI-based frailty index	Mortality, LOS, discharge disposition	Highest frailty tier: >4× odds of 30-day mortality; stepwise worse outcomes	External validation	Routes frail patients to geriatric co-management / prehab
Shelley et al – clinical utility framing	Commentary / periop risk	Emphasizes endpoint choice and timing	–	–	Predict the "right" endpoint when intervention is possible	–	Helps select deployable preop targets (e.g., PPC prevention)
Kolin et al – anemia / transfusion risk	Orthopedic surgery (TKA)	Routine clinical variables (age/sex, baseline Hb, comorbidities)	ML predictive models	Postop anemia; transfusion	AUROC 0.88–0.90	Retrospective modeling	Triggers iron/EPO, crossmatch planning; avoids low-yield testing
Jiang et al – penicillin allergy delabeling	Neurosurgical inpatients	EHR allergy history patterns	ML classifier	True allergy vs intolerance	22% labels inconsistent; reported accuracy 98%	Feasibility study	Prompts allergy consult/testing → better prophylaxis choices
Vydiswaran et al – risky alcohol detection	Preop patients (notes-based)	**Unstructured** preop clinical notes	NLP	Risky alcohol use	Detected 87% vs 29% with ICD codes	Retrospective NLP study	Earlier counseling, prophylaxis for withdrawal/delirium
Bishara et al – delirium prediction	Surgical patients	Preop EHR data	ML	Postop delirium	(Performance not detailed in current draft excerpt)	Published model	Preop geriatric pathway, medication review, non-pharm bundles
Nair et al – opioid needs prediction	Ambulatory surgery	Preop factors	ML (e.g., RF classifiers)	Postop opioid requirement	(Performance not detailed in current draft excerpt)	Published model	Guides multimodal analgesia, RA strategy, pain referral
Workflow integration (implementation principle)	Preop clinic / EHR	Risk scores + interpretability + prompts	Decision support integration	Action uptake	Needs seamless EHR integration + interpretable outputs	Real-world integration described for Mahajan model	Turns predictions into consults, optimization checklists, scheduling

prevention of other postoperative complications amenable to preoperative intervention. One important area is postoperative opioid use and the risk of prolonged opioid dependence. Nair et al. developed a machine learning model to predict postoperative opioid requirements in patients undergoing ambulatory surgery, demonstrating that algorithms such as random forest classifiers could reliably identify patients likely to require higher analgesic doses (13). Beyond immediate postoperative needs, multiple studies have shown that preoperative factors—including chronic pain syndromes, preoperative opioid exposure, and certain psychosocial variables—are strong predictors of persistent opioid use after surgery (3). AI-based clinical decision support tools could integrate these variables and provide automated alerts identifying patients at high risk for prolonged opioid use, thereby prompting early referral to pain specialists, implementation of multimodal analgesia strategies, or greater reliance on regional anesthesia techniques.

c) Diabetic Patient Optimization - Similar approaches have been explored for metabolic optimization, particularly in patients with diabetes mellitus. Machine learning models have demonstrated the ability to predict which diabetic patients are at highest risk for postoperative complications related to poor glycemic control, such as surgical site infections or delayed wound healing. These predictions can guide intensified preoperative glycemic optimization, endocrine consultation, and individualized perioperative glucose management strategies (1).

d) Smoking Cessation & Life-style Optimization - Lifestyle-related risk factors represent another critical but frequently under-recognized component of preoperative assessment. Smoking and hazardous alcohol consumption are both independently associated with increased perioperative morbidity, including pulmonary complications, wound infections, delirium, and prolonged hospitalization. Artificial intelligence applications in this domain increasingly rely on conversational agents and natural language processing. Emerging evidence suggests that AI-powered chatbots or automated messaging platforms can engage patients in smoking cessation counseling tailored to the preoperative timeline, reinforcing behavioral change during a period when patients may be particularly receptive to intervention (1). Large language models, including tools such as ChatGPT, have also been explored as adjuncts for answering patient questions and providing personalized health education prior to surgery. With respect to alcohol use, Vinod Vydiswaran et al. demonstrated the power of natural language processing applied to preoperative clinical notes to detect risky alcohol consumption. In their study, NLP algorithms identified 87% of patients consuming more than two alcoholic drinks per day, compared with only 29% identified using conventional ICD diagnostic codes, effectively tripling detection rates (14,15). This finding underscores the ability of AI to extract clinically meaningful information from unstructured text that is often missed by structured data fields. Early identification of hazardous alcohol use allows clinicians to initiate preoperative interventions such as counseling, vitamin supplementation, or withdrawal prophylaxis, thereby reducing the risk of postoperative delirium, withdrawal syndromes, and ICU admission.

e) Perioperative Patient Education - Finally, artificial intelligence is beginning to play a role in patient education and engagement during the preoperative period. Adequate preparation of patients—both physically and psychologically—is essential for optimizing surgical outcomes. Conversational AI platforms can provide individualized education about planned procedures, perioperative expectations, and recovery pathways, while also reinforcing key instructions such as fasting requirements, medication adjustments, and prehabilitation exercises. Early reports suggest that these tools may improve patient comprehension, satisfaction, and anxiety levels. Jones et al. describe how AI systems, including large language models, have been piloted to enhance preoperative education and support behavioral interventions such as smoking cessation (1). Although these applications remain in early stages of implementation, they hold promise for extending the reach of preoperative optimization beyond the clinic visit and providing continuous, scalable patient support.

Integration into clinical workflow

For AI to truly improve preoperative care of complicated patients, it must integrate seamlessly into existing workflows. This means turning predictive insights into actionable clinical steps. Some leading medical centers have begun integrating ML risk scores into preoperative clinic software or the electronic record. For instance, the model by Mahajan et al. was deployed at the point of care in a prospective trial, meaning that when a patient was seen preoperatively, the system generated a risk score in the background and identified high-risk patients to clinicians (2). Such integration allowed the care team to "optimize perioperative care" by, for example, scheduling a high-risk patient for closer intraoperative monitoring, ICU admission post-op, or preemptive specialist consultations. Another domain of integration is scheduling and resource allocation: AI algorithms can help prioritize which patients should be seen in specialized pre-op clinics (e.g., a frail patient flagged by an EHR-based frailty index might be routed to a multidisciplinary geriatric optimization program pre-surgery).

To facilitate adoption, AI outputs should be presented in a user-friendly, interpretable manner. Clinicians are more likely to trust and use an AI risk tool if it explains its reasoning (e.g., listing key risk factors contributing to a high risk score) and if it links to suggested actions (like "consider cardiology evaluation" or "optimize nutrition"). There are also efforts to incorporate AI-based checklists that automatically pull patient data and highlight gaps in optimization (for example: "Patient has Hgb 10 g/dL, anemia protocol recommended" or "BMI > 40, evaluate for weight loss program prior to elective bariatric surgery"). By acting as an ever-vigilant assistant, AI can ensure complex patients receive thorough evaluation and that modifiable issues are addressed systematically.

It's worth noting that AI doesn't act alone, but rather augments the clinician. The perioperative team (surgeons, anesthesiologists, internists) still makes the final decisions and engages patients in optimization strategies. AI's role is to provide a more informed foundation: identifying the silent risk factors, quantifying risk severity, and even predicting which interventions might yield the most benefit. In complex patients who often have numerous issues, this helps prioritize efforts on what will most improve surgical readiness and outcomes (16,17).

Challenges and future perspectives

While the promise of AI in preoperative assessment is great, there are important challenges and limitations to acknowledge.

Despite the growing enthusiasm surrounding artificial intelligence in perioperative medicine, several important challenges must be addressed before widespread clinical implementation in preoperative assessment and optimization can be achieved.

Data privacy and security - One of the foremost concerns relates to data privacy and security. Most AI models rely on large-scale datasets extracted from electronic health records, which contain highly sensitive personal and medical information. Ensuring patient privacy is therefore paramount, and AI systems must be developed and deployed in strict compliance with data protection regulations. Beyond regulatory compliance, the use of personal health data for algorithm training raises broader ethical concerns, particularly regarding secondary data use and long-term data storage. Robust anonymization techniques, secure data infrastructures, and advanced cybersecurity measures are essential to maintain institutional and patient trust in AI-driven clinical tools.

Amplification of Bias - Another major challenge is algorithmic bias and fairness. Machine learning models are inherently dependent on the data used for their training and may inadvertently reproduce or amplify existing biases present in historical healthcare data. For instance, if certain patient populations—such as women, ethnic minorities, or socioeconomically disadvantaged groups—have historically experienced poorer outcomes due to unequal access to care or systemic disparities, a naïvely trained algorithm may incorrectly assign higher risk to these groups and perpetuate inequities. This underscores the necessity of validating AI models across diverse populations and healthcare settings. Risk prediction tools must be carefully audited to ensure that they do not disproportionately penalize patients based on non-modifiable characteristics such as race or socioeconomic status. Ongoing efforts to improve fairness through bias detection, model recalibration, and transparent reporting are critical to the ethical adoption of AI in perioperative care.

Clinical skepticism and concerns about workflow disruption also represent significant barriers to adoption. Many clinicians remain cautious about integrating AI into routine practice, particularly when algorithms function as "black boxes" with limited interpretability. Fear of over-reliance on automated systems and erosion of clinical judgment is common. To address these concerns, developers increasingly emphasize explainable AI approaches that provide clinicians with insight into how predictions are generated and which variables contribute most strongly to risk estimates. User-centered design and seamless integration into existing electronic health record workflows are equally important. Early success stories, such as AI tools that demonstrably prevent complications or reduce healthcare costs, may help build confidence among clinicians. Equally crucial is structured training for perioperative teams, enabling them to interpret AI outputs appropriately and to view these tools as decision-support systems rather than decision-makers. Demonstrating that AI can reduce cognitive burden and save time by automating repetitive aspects of risk assessment will likely be key to broader acceptance among busy clinicians.

Regulatory and legal considerations further complicate the implementation of AI in preoperative medicine. When AI systems provide patient-specific recommendations, questions inevitably arise regarding responsibility and liability in the event of an adverse outcome. Regulatory agencies, including the U.S. Food and Drug Administration and their international counterparts, are beginning to develop frameworks for evaluating and approving clinical AI tools. At present, most AI applications in preoperative assessment are positioned as advisory systems, with ultimate responsibility remaining firmly with the clinician. However, as models become increasingly autonomous and adaptive, clearer regulatory oversight and legal frameworks will be required. Establishing transparent standards for validation, monitoring, and accountability will be essential to ensure patient safety and clinician protection.

Finally, there remains a substantial need for prospective evidence. Although many AI models in perioperative medicine have demonstrated impressive performance in retrospective and observational studies, relatively few have been evaluated in prospective trials or real-world implementation studies. Future research should prioritize assessing whether AI-driven preoperative assessment and optimization strategies translate into meaningful improvements in patient-centered outcomes, such as reduced complication rates, shorter hospital stays, or decreased ICU utilization, as well as demonstrating cost-effectiveness. Encouraging early data exist, including the prospective validation of large-scale risk prediction models such as the UPMC preoperative risk model described by Mahajan et al., but broader evidence is needed to firmly establish the clinical value of these tools. Ongoing research should also focus on continuous model refinement using updated data and on defining optimal strategies for integrating AI recommendations into standardized preoperative clinical pathways, potentially through guidelines that incorporate AI-based risk stratification.

Despite these challenges, the trajectory is clearly toward greater AI involvement. The future likely holds increasingly sophisticated AI systems that can aggregate data from multiple sources (EHR, wearable devices, genomics, etc.) for a 360-degree preoperative assessment. These might even simulate outcomes under different scenarios, for example, predicting "if we improve this patient's pulmonary function by X, the risk of complication drops by Y%," thus guiding specific optimization interventions quantitatively. Furthermore, AI might help in surgical decision-making, identifying patients who are at the highest risk for a procedure and therefore alternatives to be made available. By continuously learning from each surgical outcome, AI systems can become smarter and more personalized over time (18).

Conclusion

Artificial intelligence is poised to become an invaluable ally in the preoperative assessment and optimization of complicated surgical patients. By leveraging vast datasets and advanced algorithms, AI can enhance risk stratification, identify high-risk patients with greater accuracy and granularity than traditional methods. It can also aid in focusing and addressing modifiable risk factors through innovative applications like NLP-driven substance use detection, predictive models for complications, and decision support for optimization interventions (anemia management, allergy delabeling, etc.). For intensive care and perioperative professionals, these technologies offer the potential to improve patient outcomes: fewer complications, more efficient use of ICU resources, and tailored perioperative care plans. Early studies and implementations have shown promising results, such as improved predictive performance (2) and successful identification of hidden risk factors (14,19,20). Nevertheless, integrating AI into routine practice requires careful attention to ethics, bias, and user adoption. As we continue to validate these tools in diverse patient populations and refine their integration into clinical workflows, AI-driven preoperative assessment could markedly enhance the safety and effectiveness of surgery for our most vulnerable patients.

In summary, the collaboration of human clinical expertise with machine intelligence stands to optimize perioperative care, enabling precision medicine in surgical risk assessment and preparation. With ongoing research and responsible implementation, AI's full potential in perioperative medicine may transform how we evaluate and optimize complex surgical patients for the better.

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Author contribution

Study conception and design: YE, YM, RB; data collection: YE, YM, RB; analysis and interpretation of results: YE, YM, RB; draft manuscript preparation: YE, YM, RB. The author(s) reviewed the results and approved the final version of the article.

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