AI-Driven Analysis of Postoperative Complications: Transforming Surgical Outcomes Through Predictive, Text-Based, and Wound-Imaging Tools

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Abstract

Artificial intelligence (AI) has rapidly emerged as a powerful tool to analyze, predict, and detect complications after surgical interventions, leveraging large volumes of perioperative data that are difficult for humans to process alone,,. Machine learning models built on electronic health records, vital signs, intraoperative signals, imaging, clinical notes, and wound photographs can identify patients at high risk for postoperative complications such as sepsis, acute kidney injury, pneumonia, and mortality, with performance that matches or surpasses traditional risk scores and clinicians in several studies,,. Foundation models and large language models that specifically analyze surgical notes further enhance complication prediction and generalizability across settings, while AI-based wound-image analysis enables earlier detection of wound problems and prioritization of follow-up,,. This article reviews key AI tools for postoperative complication analysis, outlines their methodologies, summarizes clinical performance, and discusses integration into perioperative workflows and future directions.

Keywords: artificial intelligence, surgical complications, postoperative risk, machine learning, clinical notes, wound monitoring, predictive analytics, perioperative care

Introduction

Postoperative complications substantially contribute to morbidity, mortality, prolonged intensive care unit (ICU) stays, and healthcare costs, affecting up to one-third of surgical procedures in some series,. Traditional risk prediction relies on static scoring systems and clinician judgment, which may be limited by the complexity of perioperative data and variability in expertise,. AI and machine learning methods offer a way to integrate high-dimensional preoperative, intraoperative, and postoperative data to generate dynamic, individualized risk estimates for multiple complications simultaneously,,. Cohort studies and systematic reviews now show that AI models can achieve high discrimination for postoperative complications and 30-day mortality and can provide clinically interpretable outputs to support decision-making,,,. This review focuses on how AI tools analyze complications after surgical interventions,

including risk prediction, automated detection from clinical documentation, and remote wound monitoring.

Methods

This narrative review synthesized recent literature on AI tools used to analyze complications following surgical interventions, with a focus on validated models in perioperative care. Sources included cohort studies and systematic reviews describing machine learning or deep learning models for predicting or detecting postoperative complications, 30-day mortality, or surgical site problems,,,,. Studies using structured data (demographics, labs, vitals, surgical characteristics), unstructured data (clinical notes, operative reports), physiological signals (e.g., ECG), or wound images were considered,,,. Key outcomes extracted were type of complication analyzed, data sources, AI method, and reported performance metrics such as area under the receiver operating characteristic curve (AUC), sensitivity, and specificity.

Results

AI for risk prediction before and after surgery

Multiple machine learning models have been developed to predict overall postoperative complications and specific adverse events such as sepsis, acute kidney injury, pneumonia, deep vein thrombosis, and 30-day mortality. A cohort study of more than 100,000 operations demonstrated that models using combined preoperative and intraoperative data (including gradient boosting trees and deep neural networks) achieved high AUCs for predicting several complications, outperforming simpler linear methods. In abdominal surgery, six AI models trained on hospital data achieved strong predictive performance for 30-day mortality, with one model reaching an AUC of 0.94, sensitivity of about 0.92, and specificity of about 0.90, suggesting potential readiness for clinical use in risk stratification. Systems such as MySurgeryRisk, which automatically ingest electronic health record data (laboratory results, vital signs, medications, demographics, intraoperative variables), have been shown to predict multiple postoperative complications with accuracies comparable to or better than physicians, and to outperform surgeons in predicting certain events such as venous thromboembolism.

These AI-based risk tools can support perioperative decision-making by identifying high-risk patients who may benefit from closer monitoring, altered surgical plans, or targeted prophylaxis. For example, an AI model based on routine preoperative ECG combined with other data was able to predict postoperative complications with about 85% accuracy in one report, surpassing existing risk scores and showing that even short diagnostic tests can be leveraged by AI for risk prediction. Prognostic machine learning frameworks are also being developed to classify patients into complication versus non-complication groups using patient-, surgery-, and postoperative-related factors,

with performance evaluated through accuracy, precision, recall, and F1 score to guide optimization. Systematic evaluations of such models indicate that many achieve good discrimination but also highlight the need for robust validation and transparent reporting before widespread adoption,,.

AI on clinical notes and operative documentation

In addition to structured data, AI tools now analyze unstructured texts such as operative notes, progress notes, and multidisciplinary documentation. A foundation AI model trained on nearly 85,000 surgical clinical notes and outcomes used large language models to predict complications including pneumonia, blood clots, and infections, outperforming traditional natural language processing methods,,. For every 100 patients who experienced postoperative complications, this model correctly identified up to 39 additional high-risk patients compared with previous embedding-based approaches, demonstrating substantial gains in sensitivity,,. Importantly, this large-language-model–based system could simultaneously predict risk for multiple complication types by exploiting shared risk factors across outcomes, enabling a unified perioperative risk tool,,.

Other work has assessed machine learning approaches that combine preoperative characteristics with text-based clinical notes to predict multiple major postoperative complications, demonstrating high AUCs and showing that textual information contains prognostically relevant features not captured in structured fields. These models often use interpretable techniques such as feature importance rankings or model-agnostic explanation methods to highlight which words, phrases, or note sections strongly influence risk predictions, aiding clinician trust and integration into workflow. Together, these advances indicate that AI can transform the rich narrative content of surgical documentation into actionable predictions that help clinicians anticipate and mitigate complications.

AI in wound monitoring and remote complication detection

Postoperative wound complications, including infections and poor healing, are common and costly but often develop after discharge. Digital wound monitoring platforms with AI modules aim to detect signs of non-healing from patient-submitted images and prioritize cases for urgent review. The WISDOM feasibility trial protocol describes an AI-supported wound imaging platform in cardiac surgery patients, where an algorithm flags redness, discolouration, wound gaping, unexpected tissue or fluid, or retained sutures beyond 14 days, prioritizing concerning images for clinician review. This approach seeks to maintain safety and early detection while managing staff workload by triaging which images require immediate attention. The AI module is being evaluated for predictive performance, sensitivity, specificity, and agreement with clinicians, with the goal of informing a definitive outcome trial.

Beyond wound imaging, systematic reviews on AI for postoperative infection and surgical site infection prediction show that machine learning models built on perioperative data can reach good discrimination, though methodological quality and external validation are variable,. Automated capture of intraoperative adverse events using AI is also an emerging area, with models analyzing video, sensor data, or structured intraoperative records to identify events associated with later complications. These systems may allow near-real-time detection of operative problems, providing opportunities for immediate correction and more accurate documentation for postoperative risk assessment. Overall, AI-based remote monitoring and intraoperative event detection extend complication analysis beyond traditional static risk scores into continuous, dynamic surveillance across the perioperative timeline.

Discussion

AI tools to analyze complications after surgical interventions are moving rapidly from proof-of-concept to clinically relevant applications, particularly in risk prediction and early detection. Large cohort studies demonstrate that machine learning models integrating preoperative and intraoperative variables can achieve high predictive performance for multiple complications and 30-day mortality, often outperforming conventional scores and linear methods,,,. Systems such as MySurgeryRisk and ECG-based models illustrate that AI can leverage routinely collected data streams to provide real-time risk estimates at the bedside, potentially supporting individualized perioperative care plans,. However, successful translation requires careful external validation, calibration, clinician interpretability, and integration into existing decision pathways to avoid overreliance or alarm fatigue,,.

The use of large language models and foundation AI models on surgical notes and other unstructured clinical texts represents a major step forward in capturing the nuanced, context-rich information embedded in narrative documentation,,. By identifying additional high-risk patients beyond what structured data models can recognize, these systems may improve sensitivity for complications, particularly for conditions with subtle or multifactorial risk profiles,. At the same time, digital wound monitoring and image-based AI tools show promise in extending complication surveillance into the home, enabling earlier intervention and more efficient allocation of clinician effort,. Future work must address bias, fairness, data privacy, and model drift, and should evaluate whether AI-guided interventions actually reduce complication rates, ICU stays, mortality, and costs in randomized or pragmatic trials. Collaboration between surgeons, anesthesiologists, data scientists, and informaticians will be essential to design AI systems that are safe, transparent, and aligned with perioperative workflows.

Conclusion

AI-driven analysis of complications after surgical interventions is reshaping perioperative risk assessment from static, one-time predictions into dynamic, data-rich, and individualized decision support. By combining structured perioperative data, unstructured clinical notes, physiological signals, and wound images, modern machine learning and large language models can identify high-risk patients earlier and more accurately than traditional methods, offering opportunities for targeted prevention and closer monitoring,,,,,,. As these tools mature, the priority will shift from demonstrating predictive accuracy to showing real-world impact on complication rates, patient outcomes, and resource use, while ensuring fairness, transparency, and clinician trust. Thoughtful integration of AI into surgical practice, with robust validation and clear governance, has the potential to transform postoperative care into a safer, more proactive, and more personalized component of the patient's surgical journey.

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