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EFFECTIVENESS OF METHODS FOR PREDICTING POSTOPERATIVE COMPLICATIONS: A LITERATURE REVIEW

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Annotation

Background: Postoperative complications remain a major challenge in modern surgery, contributing to prolonged hospitalization, increased healthcare costs, morbidity, and mortality.

To review the effectiveness of traditional and modern approaches for predicting postoperative complications and to assess the potential of artificial intelligence (AI) and machine learning technologies in surgical risk stratification. A review of recent literature was performed, focusing on clinical and laboratory predictors, conventional risk scores, machine learning algorithms, electronic health records, and dynamic perioperative data.

Traditional systems such as ASA, POSSUM, P-POSSUM, and ACS NSQIP remain clinically useful but have limitations in capturing complex and nonlinear relationships among multiple risk factors. Machine learning models, including Random Forest, XGBoost, neural networks, and other algorithms, demonstrated promising predictive performance across various surgical outcomes. Models such as MySurgeryRisk and POTTER showed high discriminatory ability for postoperative complications and mortality. Integration of laboratory, physiological, intraoperative, and electronic health record data may further improve individualized risk prediction. However, substantial heterogeneity among studies, limited external validation, and the predominance of retrospective single-center studies remain important limitations. Additional concerns include data quality, class imbalance, algorithmic bias, model interpretability, and integration into clinical workflows.

AI-based prediction models have considerable potential to improve early identification of high-risk surgical patients and optimize perioperative management. Nevertheless, prospective multicenter studies, external validation, standardized reporting, and evaluation of real-world clinical effectiveness are required before widespread implementation. AI should currently be considered a clinical decision-support tool that complements, rather than replaces, professional clinical judgment.

Keywords: postoperative complications; risk prediction; artificial intelligence; machine learning; deep learning; general surgery; surgical risk assessment; predictive models; postoperative mortality; perioperative medicine.

Introduction. One of the major challenges in modern surgery is the timely detection of postoperative complications and the accurate assessment of the risk of their development. Despite significant advances in surgical techniques, anesthesiology, and intensive care, postoperative complications remain among the leading factors contributing to prolonged hospitalization, increased healthcare costs, impaired quality of life, and higher mortality [1,2].

The development of postoperative complications is a multifactorial process involving complex interactions among patient age, sex, functional status, comorbidities, nutritional status, inflammatory conditions, urgency of surgery, extent of surgical intervention, operative duration, blood loss, anesthetic risk, and postoperative physiological changes [2–4]. Therefore, assessment of the risk of

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complications in an individual patient based on a single clinical or laboratory parameter is often insufficient.

The primary objective of predictive assessment is to identify high-risk patients before surgery or during the early postoperative period, provide individualized monitoring, determine the potential need for intensive care, initiate preventive measures in a timely manner, and optimize the allocation of healthcare resources. From this perspective, a predictive model should not only demonstrate adequate statistical performance but also be clinically interpretable, robust, and externally validated in independent patient populations [3,12].

Traditional Methods for Predicting Postoperative Complications

Early approaches to predicting postoperative complications were primarily based on clinical experience, expert assessment, and scoring systems combining several risk factors. Currently, the American Society of Anesthesiologists (ASA) Physical Status Classification, POSSUM, P-POSSUM, ACS NSQIP, and other surgical risk calculators are widely used in clinical practice. Their major advantages include simplicity, transparency, ease of integration into routine clinical workflows, and rapid estimation of risk [4,14].

The ASA Physical Status Classification is used to assess the patient's overall physical condition and is widely applied in anesthesiology. However, it was not specifically designed to predict individual surgical complications. Its assessment may be influenced by subjectivity, while the type and complexity of surgery, operative duration, and intraoperative physiological changes may not be adequately reflected [3–5,11].

The POSSUM system was developed to estimate postoperative morbidity and mortality by combining physiological and operative parameters. Subsequently, the P-POSSUM model was developed to improve the prediction of postoperative mortality. However, these scoring systems rely on predefined predictors and have limited ability to account for complex nonlinear interactions among multiple risk factors [4,6].

ACS NSQIP is one of the largest national databases used for evaluating surgical outcomes and forms the basis of several widely used risk prediction tools. It enables estimation of postoperative complications and mortality based on demographic and clinical characteristics, comorbidities, and the type of surgical procedure. Nevertheless, these models have limited ability to incorporate all dynamically changing intraoperative and postoperative parameters [3].

Prediction Based on Clinical and Laboratory Parameters

Laboratory parameters play an important role in predicting postoperative complications. In particular, C-reactive protein (CRP), leukocyte and neutrophil counts, hemoglobin, albumin, creatinine, bilirubin, and coagulation parameters may provide valuable information regarding the patient's inflammatory status, nutritional condition, renal and hepatic function, and susceptibility to infectious complications [7,15].

In a study by Gataullin et al. involving patients undergoing surgery for colorectal cancer, postoperative CRP dynamics were evaluated as an important predictor of septic complications. The authors demonstrated that dynamic monitoring of CRP during the postoperative period could facilitate early risk stratification of patients according to their likelihood of developing complications [7,12].

Predicting postoperative complications in patients with obstructive jaundice is also a challenging clinical task. In a study by Pototsky, approaches based on clinical and laboratory parameters were investigated in this patient population. Impaired bilirubin metabolism, endogenous intoxication, infectious processes, and organ dysfunction were considered important factors contributing to postoperative risk [8].

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However, the isolated use of laboratory markers also has limitations. For example, an elevated inflammatory marker does not necessarily indicate the presence of a specific surgical complication. Therefore, combining laboratory parameters with clinical, physiological, and operative variables may improve the overall accuracy of postoperative risk prediction [2,13].

Prediction of Specific Surgical Complications

Postoperative complications can manifest in various clinical forms. These include surgical site infection, anastomotic leakage, postoperative bleeding, sepsis, respiratory failure, cardiovascular complications, acute kidney injury, and prolonged need for intensive care. Because the risk factors differ substantially among individual complications, development of a single universal predictive model remains challenging [12].

Specific scoring systems and predictive models have been developed to estimate the risk of severe postoperative complications in pancreatic and hepatobiliary surgery. In particular, the PREPARE score has been investigated for the prediction of severe complications following pancreatic surgery. The major advantage of procedure-specific models is their ability to incorporate risk factors that are particularly relevant to a specific type of surgical intervention [9].

In a study by Panin et al. involving patients with perforated peptic ulcers and malignant diseases, a predictive model was developed to estimate postoperative complications and mortality. The model demonstrated a sensitivity of 85.7% and a specificity of 97.4%. The authors emphasized that stratification of patients according to their individual risk level may improve the prediction of postoperative outcomes [10].

Mathematical Models and Statistical Prediction

Multivariable logistic regression is one of the most widely used approaches for developing classical predictive models. This method identifies several independent variables statistically associated with a postoperative outcome and uses them to calculate an individual's risk. An important advantage of regression-based models is their interpretability and the possibility of translating their results into clinically meaningful risk estimates [4,11].

However, logistic regression models generally require assumptions regarding the form of the relationship between predictors and outcomes. When complex nonlinear relationships exist among clinical variables, conventional regression models may not fully capture these interactions [1,14].

Another area of mathematical modeling involves decision trees and fuzzy-logic models. Such approaches can be particularly useful in clinical decision-making because they allow multiple factors to be considered simultaneously. Russian studies have also investigated fuzzy mathematical models for assessing postoperative risk and supporting individualized surgical decision-making [12].

Development of Machine Learning Technologies

Over the past decade, the rapid growth of electronic healthcare data has accelerated the application of machine learning technologies to surgical risk prediction. Machine learning enables the automated identification of complex patterns within large datasets. Random Forest, Gradient Boosting, XGBoost, Support Vector Machine, artificial neural networks, and other algorithms have been increasingly investigated for predicting surgical outcomes [1,7].

In a 2021 systematic review by Elfanagely et al., studies published between 2015 and 2020 were analyzed. Of the initially identified 2,677 publications, 45 met the inclusion criteria. The most frequently used algorithms were Random Forest, artificial neural networks, and logistic regression. The authors concluded that machine learning has substantial potential for individualized prediction of surgical outcomes, while emphasizing considerable heterogeneity in study quality, methodology, and validation strategies [1,8,9].

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A systematic review by Stam et al. focusing on major abdominal surgery identified 1,537 publications, of which 15 studies were included in the final analysis. Across these studies, artificial intelligence-based approaches were used to predict postoperative complications and mortality. Reported sensitivity ranged from 0.06 to 0.96, specificity from 0.61 to 0.98, accuracy from 0.78 to 0.95, and area under the receiver operating characteristic curve (AUROC) from 0.50 to 0.96.

The authors concluded that artificial intelligence algorithms have considerable potential for predicting postoperative complications; however, adequate internal and external validation remains essential. Complete and high-quality datasets, as well as appropriate management of class imbalance, are important prerequisites for reliable predictive performance [2,6].

Prediction Using Electronic Health Records

Electronic health records (EHRs) are becoming an important source of information for artificial intelligence-based predictive models. They may contain demographic characteristics, medical history, laboratory results, comorbidities, medications, operative information, and physiological parameters. Automated processing of these data enables the development of individualized patient risk profiles [5,11].

Hill et al. developed an automated machine learning model using data from 53,097 surgical patients to predict in-hospital postoperative mortality based on readily extractable preoperative EHR data. The model demonstrated an AUC of 0.932 and showed strong discriminative performance compared with established clinical risk measures [5,14].

In another study, an Elastic Net model based on EHR data was developed to identify postoperative complications. The model achieved a sensitivity of 83%, specificity of 88%, and an AUC of 0.93. These findings suggest that artificial intelligence may be useful not only for preoperative risk prediction but also for automated identification of postoperative complications through continuous electronic monitoring [6,9].

The Pythia model investigated the prediction of postoperative complications using automatically extracted EHR data. The system was developed using a database containing more than 37 million clinical encounters and incorporated 194 clinical features. A simplified calculator was subsequently developed to facilitate potential clinical application [13].

The MySurgeryRisk Model

One of the most widely recognized applications of artificial intelligence in surgical risk prediction is MySurgeryRisk. Bihorac et al. developed and validated this machine-learning model using data from 51,457 adult surgical patients. The model was designed to predict major postoperative complications, including acute kidney injury, sepsis, venous thromboembolism, prolonged intensive care unit stay, prolonged mechanical ventilation, wound complications, neurological and cardiovascular complications, as well as mortality [3]. The original study was published in Annals of Surgery in 2019.

MySurgeryRisk provides individualized estimates of surgical risk in the form of patient-specific probabilities. One of its major advantages is its ability to utilize information routinely available in electronic health records. However, because the original model was developed using data from a single clinical center, external validation in other healthcare settings is essential before widespread implementation [3].

The POTTER Model and Emergency Surgery

Predicting postoperative complications in emergency surgery is particularly challenging because patients often present in severe clinical condition and there is limited time available for decision-making. To address this problem, Bertsimas et al. developed the Predictive OpTimal Trees in Emergency Surgery Risk (POTTER) model [14].

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POTTER uses a machine-learning-based tree approach to predict 30-day mortality and morbidity in emergency surgery. In its development study, data from 382,960 emergency surgery patients were analyzed. The model demonstrated a mortality c-statistic of approximately 0.92 and a morbidity c-statistic of approximately 0.85, outperforming several conventional risk assessment tools.

An important advantage of the POTTER model is its relatively interpretable and user-friendly structure. Therefore, the model may potentially serve not only as an automated prediction tool but also as an aid in discussing surgical risks with patients and their families [4,14].

Importance of Intraoperative Data

The risk of postoperative complications is not determined exclusively by preoperative variables. Changes in blood pressure, heart rate, oxygen saturation, blood loss, operative duration, and other physiological parameters during surgery may substantially influence postoperative outcomes [3,15].

In a large study involving 111,888 surgical procedures, machine learning algorithms were applied to preoperative and intraoperative data to predict postoperative complications, including pneumonia, acute kidney injury, deep vein thrombosis, pulmonary embolism, and delirium. The findings suggested that incorporation of intraoperative information may improve the predictive performance of selected models [15].

Deep learning models using dynamic physiological data are particularly promising. A time-series-based deep learning model developed using data from 95,907 patients achieved an AUC of 0.867 for predicting 30-day postoperative mortality and demonstrated better performance than conventional neural networks, Random Forest, Support Vector Machine, and logistic regression models [1,6].

Advantages of Machine Learning Compared with Logistic Regression

The principal theoretical advantage of machine learning models is their ability to identify complex and nonlinear relationships among multiple predictors. However, it would be inappropriate to conclude that machine learning automatically outperforms logistic regression in every clinical setting [1,7].

A 2024 systematic review and meta-analysis analyzed 38 studies involving 62 logistic regression models and 143 machine learning models for predicting postoperative outcomes in gastrointestinal surgery. On average, the best-performing machine learning models demonstrated an AUC that was 0.07 higher than that of logistic regression models, with the difference being statistically significant [7].

However, approximately half of the included studies were considered to have a low risk of bias. Therefore, superior discrimination of machine learning models should not automatically be interpreted as evidence of improved clinical effectiveness or better patient outcomes [1,4,7].

Prediction of Surgical Site Infection

Surgical site infection (SSI) is one of the most common postoperative complications and is associated with prolonged hospitalization and increased healthcare costs. The use of machine learning algorithms for predicting and detecting SSI has therefore attracted considerable research interest [1,8].

A systematic review and meta-analysis of methods for identifying and predicting SSI analyzed 32 studies and 108 algorithms from 945 initially identified publications. Algorithms combining structured clinical data with textual information demonstrated higher sensitivity and AUC than models based solely on structured data. Nevertheless, the authors emphasized the need for external validation before implementation in routine clinical practice [5,8].

These findings highlight the importance of integrating multiple data types when predicting postoperative complications. Simultaneous analysis of laboratory parameters, operative information,

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and clinical text contained in electronic health records may enable more accurate individual risk assessment [6,8].

Machine Learning in Colorectal and Abdominal Surgery

In colorectal surgery, machine learning models have been investigated for predicting complications such as anastomotic leakage, infection, prolonged hospitalization, and readmission. Recent studies have increasingly focused on relatively uncommon but clinically severe outcomes, such as anastomotic leakage [9].

A 2024 systematic review and meta-analysis of machine learning models in gastrointestinal surgery analyzed 38 studies and demonstrated that machine learning models generally showed better discriminative performance than logistic regression models [7].

In a separate study of laparoscopic colectomy, Random Forest, XGBoost, and other machine learning approaches were compared with logistic regression for predicting postoperative morbidity. In that relatively limited dataset, no substantial differences were observed between the models. This finding indicates that the effectiveness of machine learning depends not only on the selected algorithm but also on the size, completeness, and quality of the available dataset [9].

The Problem of External Validation

A high AUC or accuracy obtained during model development is not sufficient to justify implementation in clinical practice. A predictive model should also be evaluated in an independent population, such as patients treated at another hospital or healthcare system and under different clinical conditions [2,10].

Systematic reviews of machine learning-based prediction models in perioperative medicine have shown that many studies are single-center investigations and that external validation is frequently insufficient. This represents one of the major barriers to transferring predictive models into different clinical environments [11].

Studies involving automated prediction of surgical site infection have demonstrated the importance of assessing model generalizability through external validation across different healthcare institutions. Such approaches emphasize that external validation should be considered an essential stage in the development of clinical artificial intelligence models [11].

Model Interpretability

Another major challenge associated with artificial intelligence models is the interpretability of their predictions. For a surgeon, simply receiving a statement such as “high risk of complications” may not be sufficient. The clinician should understand which factors contribute most strongly to the predicted risk and, where possible, which interventions could reduce that risk [10].

Consequently, explainable artificial intelligence (XAI) has become increasingly important in modern predictive modeling. These approaches can identify the relative contribution of individual variables to a model's prediction. Such information may increase clinicians' confidence in model outputs and facilitate clinical decision-making [15].

Data Quality and Algorithmic Bias

The performance of an artificial intelligence model is directly dependent on the quality of the data used for model development. Missing data, incorrect coding, selection bias, class imbalance, and inaccurate outcome classification may reduce model reliability [12].

Class imbalance is particularly problematic when predicting relatively rare complications. If the prevalence of a complication is low, a model may classify most patients as “without complications” and consequently demonstrate high overall accuracy while having poor sensitivity for identifying high-risk patients [2].

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Therefore, assessment of predictive models should not rely exclusively on accuracy or AUROC. Sensitivity, specificity, positive predictive value, negative predictive value, precision-recall curves, and calibration should also be evaluated [2,12].

Reporting Standards for Predictive Models

The lack of standardization in the development and reporting of clinical prediction models represents another important methodological problem. The selection of predictors, management of missing data, division of training and test datasets, and methods of internal and external validation may vary considerably between studies [1].

In 2024, the TRIPOD+AI statement was published, providing updated recommendations for reporting clinical prediction models developed using regression and machine learning methods. These recommendations aim to improve transparency, reproducibility, methodological quality, and comparability between studies [2].

Artificial Intelligence and Clinical Decision-Making

When considering the role of artificial intelligence in clinical practice, it is more appropriate to view AI as a clinical decision-support technology rather than as a replacement for the physician. Models such as POTTER may assist clinicians in discussing perioperative risk with patients and their families [14].

At the same time, model predictions may not always correspond to clinical judgment. Individual patient characteristics, intraoperative circumstances, the surgeon's clinical experience, and the resources available within a healthcare institution all influence decision-making. Therefore, artificial intelligence should not completely replace the professional judgment of the surgeon or other healthcare specialists [15].

The Role of Russian-Language Studies

Studies by Russian authors have also investigated various approaches to predicting postoperative complications. These include the use of postoperative CRP dynamics in colorectal surgery, clinical and laboratory predictors in patients with obstructive jaundice, the PREPARE score in pancreatic surgery, and specific predictive models for patients with perforated ulcers and malignant diseases [1–4].

Burlov et al. investigated the use of the PREPARE score to predict severe postoperative complications in pancreatic surgery. This study demonstrates the potential value of developing procedure-specific risk models for individualized patient stratification [3].

Overall, the Russian-language literature indicates that laboratory biomarkers, mathematical models, prognostic scoring systems, and advanced computational approaches have been investigated for postoperative risk prediction. However, many of these models have been developed for specific diseases or patient populations, which limits their universal applicability to general surgical practice [1–4].

Comparative Assessment of Predictive Methods

The literature demonstrates that traditional scoring systems and artificial intelligence models have distinct advantages and limitations. The main advantages of traditional scoring systems are their simplicity, transparency, and extensive clinical experience of use. However, they are often based on static variables and have limited ability to account for complex nonlinear interactions among risk factors [4].

Machine learning models offer the advantages of processing large datasets, integrating numerous predictors, and identifying complex relationships among variables. Nevertheless, their performance is highly dependent on data quality, their predictions may be difficult to interpret, and their performance may decline when applied to external populations [1,2].

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The 2024 meta-analysis demonstrated an average improvement in AUC for machine learning models compared with logistic regression in gastrointestinal surgery. However, this advantage was not consistent across all studies; in some limited datasets, little or no meaningful difference was observed between machine learning and logistic regression [7,9].

Therefore, it would be inappropriate to consider any single algorithm as the universally "best" approach for predicting postoperative complications. Model selection should depend on the target population, type of surgery, volume and quality of available data, outcome being predicted, and specific clinical objective [1,7].

Future Research Directions

The use of multimodal and dynamic artificial intelligence models represents a promising direction for future research in postoperative complication prediction. Such models may integrate demographic characteristics, medical history, laboratory findings, physiological parameters, electronic health record data, intraoperative variables, and postoperative longitudinal information [5,6].

An important advantage of dynamic models is that patient risk can be recalculated continuously rather than only once. This approach may improve the early detection of rapidly developing complications such as sepsis, respiratory failure, acute kidney injury, and other forms of postoperative deterioration [5,12].

Future research should focus on large prospective multicenter studies, external validation across different countries and healthcare institutions, data standardization, and integration of predictive models into electronic health record systems. It is also important to evaluate the real-world clinical impact of artificial intelligence, including whether implementation of these models reduces complications, mortality, length of hospital stay, and healthcare costs [2,7,10].

Conclusion

The literature demonstrates that predicting postoperative complications remains an important clinical challenge in modern surgery. Although traditional risk prediction systems such as ASA, POSSUM, P-POSSUM, and ACS NSQIP continue to play an important role in clinical practice, their ability to fully capture complex, nonlinear, and dynamic clinical processes is limited [1,4].

Machine learning and artificial intelligence technologies provide new opportunities for individualized prediction of postoperative complications. Models such as MySurgeryRisk and POTTER have demonstrated strong discriminative performance using large volumes of electronic clinical data. Recent meta-analyses in gastrointestinal surgery have also shown that machine learning models may demonstrate better predictive discrimination than conventional logistic regression in selected clinical settings [3,4,7]. The MySurgeryRisk model and POTTER calculator have been specifically developed and validated for major surgical and emergency surgical populations, respectively.

However, a high AUC or accuracy does not automatically indicate that an artificial intelligence model is ready for routine clinical implementation. Insufficient external validation, the predominance of single-center studies, data quality issues, algorithmic bias, limited interpretability, and difficulties integrating models into clinical workflows remain important challenges [2,10].

Accordingly, a promising future approach to postoperative complication prediction may involve multimodal, dynamic, and explainable artificial intelligence systems. Such systems could integrate individual patient characteristics, intraoperative events, and postoperative physiological changes to provide near-real-time risk assessment [5,6].

At the current stage, artificial intelligence should primarily be regarded as a clinical decision-support technology rather than a replacement for professional clinical judgment. Its principal role

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should be the early identification of high-risk patients, individualization of preventive and therapeutic interventions, and optimization of postoperative monitoring [4,13].

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