

Machine Learning Algorithms Improve Blood Utilization in Surgical Transfusion Management

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Red blood cell transfusions are essential in perioperative care but are frequently overutilized, increasing costs and exposing patients to unnecessary harm. Traditional transfusion risk scores lack the precision needed for personalized care, often not accounting for the complexity of patient-specific variables. Machine learning (ML) has emerged as a promising tool to improve the accuracy of transfusion risk prediction by analyzing large, complex datasets and identifying non-linear relationships among clinical factors. A comprehensive review of published ML-based transfusion prediction models was conducted, focusing on surgical applications in cardiac, orthopedic, and general procedures. Studies were analyzed based on algorithm type, performance metrics, input variables, and model transparency. Implementation challenges, including data quality, clinical acceptance, and infrastructure limitations, were also examined. ML enables more accurate, individualized prediction of perioperative transfusion needs. ML models outperformed traditional methods in predictive accuracy, particularly those built using large data sets and ensemble techniques such as gradient boosting. Simpler models like logistic regression performed well with smaller datasets. Barriers to implementation included fragmented electronic health records, variability in data standardization, and limited external validation. The “black-box” nature of some ML algorithms poses additional implementation challenges for providers including trust and adoption. For successful clinical integration, models must be transparent, validated across diverse populations, and supported by standardized, high-quality data. ML-based transfusion prediction models improve blood utilization and enhance surgical outcomes.

Keywords: Perioperative blood transfusion, machine learning, risk prediction, blood utilization

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Introduction

Transfusion services in a hospital aim to provide an adequate blood product supply to patients. Maintaining a healthy inventory of blood products is a critical responsibility, ensuring their availability and prompt delivery to patients in need.¹ However, despite their life-saving potential, blood products are often used unnecessarily. While generally safe, blood transfusions carry inherent risks to patient health and contribute to increased costs for both patients and healthcare institutions.^{1,2} To mitigate unnecessary transfusions, hospitals have implemented various strategies, such as restrictive transfusion guidelines, aiming to optimize blood utilization and ensure that only patients with clinical necessities receive transfusions.

While unexpected bleeding situations can arise, pre-planned surgeries offer an opportunity to anticipate and manage transfusion needs. Accurate prediction of transfusion requirements in surgical patients is essential for effective resource allocation and planning.³ Traditionally, clinicians rely on preoperative hemoglobin (Hgb) levels, surgical risk factors, and clinical judgment to guide transfusion decisions.^{4,5} However, these methods are not always dependable, as human error and practice variability can lead to inconsistencies. Additionally, even when transfusion guidelines are unmet, clinicians may still request blood products preemptively as a precaution, resulting in unnecessary reservations and potential waste of resources.^{5,6} Addressing these challenges requires more precise and data-driven approaches to improve transfusion practices in the surgical setting.

Machine Learning (ML), a branch of artificial intelligence (AI), offers a promising solution by using electronic health data to find patterns and accurately predict transfusion needs.^{4,7,8,9} By analyzing clinical and demographic factors, ML algorithms can assist clinicians in making data-driven, patient-specific decisions regarding blood product utilization. As healthcare continues to embrace digital

transformation, integrating ML into perioperative transfusion practices has the potential to enhance decision-making, reduce unnecessary blood use, and improve patient care. ML algorithms accurately predict transfusion needs for surgical procedures, leading to improved blood utilization and patient outcomes.

Background

Blood transfusions are a lifesaving procedure made possible through voluntary blood donations.¹ Maintaining an adequate blood product inventory is a critical responsibility of transfusion services, ensuring prompt availability. However, while transfusions are essential in many clinical scenarios, their use must be evaluated to prevent unnecessary administration and associated risks. Over the past few decades, organizations like the World Health Organization (WHO) and Association for the Advancement of Blood & Biotherapies (AABB), have emphasized the use of patient blood management (PBM) programs to optimize transfusion practices and reduce inappropriate use of blood products.^{10,11}

Although they are generally safe, unnecessary transfusions pose significant health risks to patients. Patients receiving unwarranted transfusions are exposed to potential adverse effects, including transfusion reactions, transfusion-associated circulatory overload, and alloimmunization.¹⁰ Additionally, inappropriate transfusions have been associated with prolonged hospital stays, increased healthcare costs, and resource waste. A study evaluating transfusion appropriateness in 15 hospitals found that nearly 50% of transfusions were deemed unnecessary.² Despite national and institutional efforts to implement restrictive transfusion strategies, unexplained variations in transfusion practices remain, particularly in noncardiac surgeries.¹² The persistence of inappropriate transfusions raises questions about the effectiveness of guidelines, clinician adherence, and potential gaps in transfusion education. Addressing these challenges is essential to ensuring both

optimal patient outcomes and the efficient use of a limited resource.

Predicting the need for transfusion in the perioperative setting is essential for effective blood inventory management.^{3,12} Hospital transfusion services allocate substantial resources to managing surgical transfusions, including testing, preparation, and distribution of blood products. Each unit of blood transfused during surgery requires approximately 30 minutes of preparation by a medical laboratory professional.³ Preoperative evaluation of surgical patients enables the identification of transfusion risk factors, allowing clinicians to optimize management strategies before surgery or arrange for blood product availability.

Early identification of patients at substantial risk for transfusion facilitates prompt interventions, such as anemia management, and enables the use of autotransfusion techniques, such as cell salvage, in eligible patients.³ Furthermore, restricting blood product preparation to those patients with actual need prevents unnecessary sequestration of units from the blood supply inventory. However, despite perioperative transfusion guidelines, studies suggest that risk assessment tools and ordering practices are inefficient in accurately predicting transfusion needs.^{6,12,13} This inefficiency underscores the need for improved predictive models that integrate patient-specific variables, surgical factors, and laboratory data to enhance decision-making and reduce unnecessary transfusions.

Guidelines for transfusion

Effective surgical preparation is critical for ensuring patient safety and optimizing clinical outcomes. Before surgery, the surgical team evaluates the patient's clinical status, including laboratory results, to confirm readiness for the procedure. Blood management in the perioperative setting is guided by HgB thresholds and transfusion risk scores, which vary based on the type of surgery.^{4,14} Transfusion guidelines recommend a HgB threshold of 8 g/dL for patients undergoing cardiac or ortho-

pedic surgery, as well as those with pre-existing cardiovascular conditions.¹⁵ However, making the right decisions about blood product use is complex, and transfusion should not be solely based on laboratory values.

Transfusion risk scores can help predict perioperative blood requirements for different surgical procedures. One widely used tool is the Maximum Surgical Blood Ordering Schedule (MSBOS).¹⁶ This system estimates the historical RBC transfusion rates for specific procedures based on Current Procedural Terminology (CPT) codes, providing an average transfusion requirement per surgery. Institutions typically set a threshold—often at 5%—to determine whether a type and screen (T&S) test is necessary.¹⁷ If the historical transfusion rate for a procedure exceeds the threshold, a preoperative T&S is recommended. Conversely, if the likelihood of transfusion is below 5%, routine T&S may not be needed unless specific risk factors exist, such as a positive antibody screen or the use of anticoagulants and antiplatelet agents.¹⁷

Implementing the MSBOS has proven efficient in reducing the amount of blood product orders.⁶ However, one limitation is that these calculations are not frequently updated and do not account for variability in provider-specific or patient-specific characteristics.^{17,18} Surgical techniques vary among providers, affecting transfusion needs, making it essential to incorporate individual provider transfusion history into preoperative evaluations. Additionally, adherence to MSBOS recommendations remains low, as some clinicians override the system, relying instead on personal judgment to ensure blood availability.^{17,19}

The provider's intuition and clinical experience significantly influence perioperative blood product ordering.¹⁹⁻²¹ Studies reveal inconsistencies in transfusion practices for adult surgical patients, suggesting that decision-making extends beyond objective clinical data. Factors such as the providers' training, past experiences, and clinical intuition contribute to transfusion decisions.²² Research

shows that provider judgment can independently predict surgical outcomes, highlighting the complex interplay between standardized guidelines and individualized clinical assessment.

Although transfusion risk scores and clinical guidelines provide a structured framework, they allow room for provider discretion.¹⁵ A key metric for evaluating transfusion ordering practices is the crossmatch-to-transfusion (C/T) ratio.¹⁰ A high C/T ratio – where cross-matched RBC units stay unused – suggests over-ordering of blood products in the perioperative setting. When surveyed, surgeons with high C/T ratios cited concerns about delays in blood availability from transfusion services as a primary reason for ordering blood in advance as a precautionary measure.¹³

Traditional statistical models underpin many of these transfusion decision tools, but they come with limitations. These models require strict assumptions, such as linear relationships between variables, which may not always align with real-world clinical conditions. Traditional regression analyses evaluate predictors independently or within predefined subsets based on prior knowledge, often overlooking interactive effects between variables.²³ This can lead to the omission of significant predictors, reducing the model's accuracy and effectiveness in transfusion decision-making. Advancements in ML and data-driven approaches may offer improved predictive models that better reflect the complexity of perioperative transfusion needs.

Considerations for cardiac surgeries

Cardiac surgeries account for a considerable proportion of RBC use in transfusion services due to their invasive nature, high-dose anticoagulation, and exposure to cardiopulmonary bypass.^{24,25} The need for RBC transfusion in cardiac procedures varies widely, with approximately 15% of patients requiring large volumes of blood, while more than half do not require transfusion at all. This high-risk subset represents 80% of all blood products used in cardiac surgery, underscoring the importance of accurately predicting not just

transfusion likelihood but also the number of RBC units required.²⁵

Transfusion risk assessment in cardiac surgery involves multiple risk actors and patient-specific characteristics. Two widely validated tools are the Transfusion Risk Understanding Scoring Tool (TRUST) and Transfusion Risk and Clinical Knowledge (TRACK). TRACK, developed in Italy, predicts transfusion risk based on 5 preoperative factors: age, weight, sex, surgical complexity, and preoperative hematocrit (HCT) level.²⁶ TRUST, developed in Canada, incorporates 8 factors: HgB level, body weight, sex, age, emergency status, creatinine level, prior cardiac surgery, and procedural complexity.²⁷

A systematic review compared the predictive values of different transfusion risk predictive models using c-statistics, or its parallel, area under the receiver operating characteristic curve (AUC) values, where 0.5 represents random chance and 1.0 represents perfect prediction.²⁴ Nine different models were found in the literature. However, due to poor reporting and substantial risk of bias, only 2 models, TRUST and TRACK were evaluated. Both TRUST and TRACK showed moderate predictive accuracy, with c-statistics of 0.74 and 0.72, respectively. The models also seemed to slightly overestimate the number of patients needing a transfusion. Additionally, this systematic review found performance variability of the scores among studies, as ordering perioperative transfusion is influenced by differences in adherence to PBM guidelines, population characteristics, and provider-driven decision-making.²⁴

Beyond patient-related variation, recent studies highlight increasing provider-related discrepancies in RBC ordering, even when risk scores are implemented in the institution.^{21,24} Given the high frequency of transfusions in cardiac surgery, refining predictive tools to incorporate detailed patient data, provider-specific variability, and ML algorithms could enhance the accuracy and clinical utility of transfusion decision-making. Developing a more dynamic and adaptable prediction model

could lead to improved transfusion planning and better resource utilization.

Considerations for orthopedic surgeries

Preoperative anemia is a common concern in orthopedic patients, particularly due to their advanced age, which increases the risk of perioperative transfusions.²⁸ Additionally, the growing use of oral anticoagulants in the elderly population presents further challenges in managing blood loss and transfusion needs. Given the complexity of care, providers cannot rely solely on HgB thresholds when making transfusion decisions.

Total knee arthroplasty (TKA) and total hip arthroplasty (THA) rank among the most performed orthopedic surgeries worldwide.^{29,30} These procedures can lead to significant blood loss, with up to 46% of patients requiring RBC transfusions either during or after surgery.²⁹ Importantly, postoperative blood transfusions are linked to extended hospital stays and a higher risk of complications related to both transfusion and reduced mobility. Orthopedic surgeons have adopted measures to mitigate transfusion risk, including tranexamic acid administration and autotransfusion devices, though these strategies introduce their own risks and challenges.³⁰

Given the multifactorial nature of transfusion risk in orthopedic surgery, rigid guidelines may not always be practical.²⁸ Key predictors of transfusion include advanced age, low body mass index (BMI), low preoperative HgB levels, and the use of surgical drains.²⁹ By integrating these factors alongside procedure-specific variables, clinicians can develop personalized transfusion plans that refine blood management, reduce costs, and enhance patient safety. Leveraging ML and advanced predictive modeling could further refine these estimations, enabling more efficient perioperative blood utilization.

Machine learning and surgical transfusion risk prediction

Computational technology and electronic data are transforming healthcare.^{4,7,8} Artificial intelligence (AI) is a broad field encompassing

machines capable of making decisions and performing complex, human-like tasks. Within AI, pattern recognition from large and complex datasets is being increasingly applied in the healthcare field.

Machine learning (ML), a subset of AI, enables systems to learn from data in a manner similar to human learning, improving performance over time.^{4,7,8} There are 3 types of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning. Supervised ML, a statistical method widely used for predictive modeling, employs algorithms to classify data and perform regression analysis. These models are trained using historical electronic health records, finding patterns in patient characteristics and procedural details to make accurate predictions for future cases.

In the context of transfusion risk prediction for surgical patients, ML models analyze years of surgical data, incorporating procedure characteristics, patient demographics, laboratory results, surgeon-specific factors, and historical blood product usage.⁴ The type and amount of data is unlimited. In fact, the learning process of ML benefits from vast amounts of data to perform a more accurate prediction, as long as the data is well organized and defined.^{4,8,9,31} By leveraging institutional data, ML algorithms can uncover novel patterns and associations, enabling tailored risk assessments.

The most effective ML techniques used for transfusion risk prediction are supervised regression models, including single logistic regression (LR) algorithms, Gaussian processes, and decision trees, or ensemble methods, such as gradient boosting (GB) and random forest.^{4,8} These supervised ensemble methods use a combination of different ML algorithms to enhance prediction accuracy when a large amount of data is used. While the models differ in their mathematical approaches and simplicity, they share the fundamental ability to recognize complex patterns within data.

A primary challenge of ML models is their interpretability. Many advanced models function as "black boxes," making it difficult to

understand the reasoning behind their predictions. However, ML's main value relies on its ability to analyze extensive datasets for the identification of transfusion trends linked to individual surgeons, surgical techniques, and institutional blood utilization patterns. Published ML models have shown high predictive accuracy, as measured by AUC, c-statistics, and other performance metrics (Tables 1, 2, and 3). To upset the lack of transparency, ML model developers work on creating programs to explain the ML prediction. Transparency is a valuable asset to help providers trust the ML models.

Most of the published ML models are tailored to orthopedics and cardiac surgeries due to the high incidence of blood transfusions during these procedures and their unique patients' characteristics. Few models have been developed and validated for broader surgical applications (Table 1). Lou et al. created and published S-PATH, a GB ML model trained with data from years of elective surgical encounters from multiple hospitals across the United States.¹⁴ S-PATH innovation incorporates patient and surgery-specific variables in the building of predictive algorithms. By analyzing a large multi-institutional dataset with diverse transfusion practices, S-PATH translates general procedure-based transfusion risks into personalized predictions based on patient comorbidities and preoperative laboratory results. The most significant variables identified are a high MSBOS and low HCT. The model has an outstanding predictive performance and is one of the few models that has been externally validated.¹⁴

When applied in different hospitals, the S-PATH model adjusts to local transfusion rates while refining risk estimation based on patient-specific factors. A subsequent external validation study further assessed the model's performance in a variety of hospital settings.³ While incorporating hospital-specific transfusion rates slightly improved accuracy, model effectiveness varies significantly among institutions, underscoring the need for local validation before implementation. Building on this work,

other researchers have explored ML approaches tailored to specific surgical populations to enhance predictive performance.³²

Park et al. focused on developing a ML classifier to predict intraoperative transfusion risk specific for noncardiac surgeries.³² In this single center study, the main variables identified that influence the need for transfusion are operation time, preoperative Hgb level, and open surgery. Longer surgeries are linked to higher transfusion risks due to complexity, complications, and patient factors. The model accounts for different surgery durations and allows surgeons to input expected longer times for better accuracy. Preoperative anemia and open surgery are also strong independent risk factors. Other factors like prothrombin time, sodium levels, and age play a smaller role, but ML enhances predictions by considering multiple variables, even if their clinical significance is not fully understood.³²

Machine learning models for cardiac surgeries

Several ML models have been developed for transfusion risks during cardiac surgery (Table 2). Wang et al. designed an ML-based model for estimating RBC transfusion needs in cardiothoracic procedures.³³ This model use LR algorithms and demonstrates strong predictive performance for cases involving 0 to 3 RBC units transfused but its accuracy diminishes when predicting transfusions of 4 or more units. Despite this limitation, the model is still valuable for blood inventory management, as it accurately predicts transfusion requirements using only preoperative variables.³³ The use of preoperative variables in the ML models allows for their comparison with traditional risk scores in different populations.

To compare the prediction ability of TRACK and TRUST cardiac transfusion risk scores and ML algorithms in the Brazilian population, Cunha et al. developed an LR-ML model trained on local patient data, where age and body surface area (BSA) are the top variables influencing transfusion needs.¹⁸ Despite using a smaller dataset than previous studies, the LR-

Table 1. Published Machine Learning Models for Surgery

Study	Characteristics	Number of cases		Type of validation	Prediction accuracy	Significant variables found	Type of ML used	Inter-pretable design
		Training	Validation					
Lou et al, ¹⁴ 2022	Multicenter. 722 hospitals in US. Surgical cases.	2,439,694	16,053	External	c-statistic: 0.938	- MSBOS* - Hematocrit* - Platelet count - INR - PTT - Creatinine - Sodium - Albumin - Bilirubin - Patient demographics - Patient comorbidities	Gradient boosting machine	Yes
Lou et al, ³ 2024	NA.	NA.	1,000,927	External. Multicenter. 414 hospitals in US.	AUC using hospital-specific priors: 0.9246 AUC using NSQIP-wide priors: 0.9100	NA.	NA.	NA.
Park et al, ³² 2025	Single center. South Korea. Noncardiac surgery patients	4378	1877	Internal	AUC: 0.836	- Operation time* - Preoperative Hgb* - Surgical approach - open surgery* - ASA physical status - Emergency operation - PFT - mild Obstructive panel - Preoperative AST, BUN, Creatinine - Operation type - stomach	LR	No

Abbreviations: MSBOS, Maximum Surgery Blood Ordering Schedule; INR, International Normalized Ratio; PTT, activated partial thrombin time; NA, not applicable; AUC, area under the curve; NSQIP, National Surgical Quality Improvement Program; Hgb, hemoglobin; ASA, American Society of Anesthesiologists; PFT, pulmonary function test; AST, alanine aminotransferase; BUN, blood urea nitrogen; LR, logistic regression.

*Most meaningful variables.

Table 2. Published Machine Learning Models for Cardiac Surgery

Study	Characteristics	Number of cases		Type of validation	Prediction accuracy	Significant variables found	Type of ML used	Interpretable design
		Training	Validation					
Wang et al,33 2022	Single center. USA. CT surgery	2,410	437	Internal	AUC: 0.826	- ECMO initiation - ECMO continuous - ECMO cannulation - Thoracoab Dominal aortic aneurysm repair - Barometric Pressure (blood gas analysis) - Potassium - Ionized calcium - Hgb - Alb - RV >96h	GPR	No
Cunha CBC, et al,18 2024	Single center. Brazil. Cardiac surgery	396	99	Internal	AUC: 0.735	- Age* - BSA* - Hgb* - Gender* - Prior cardiac surgery - Use of CPB	LR	Yes
Hur et al,9 2024	Single center. Republic of Korea. Thoracic surgery	6,200	1,643	Internal	RMSE: 3.203 R2: 0.399	- MSBOS* - Hgb* - PT - Platelet count - Comorbidity (cancer) - PTT - Comorbidity (renal disease) - Comorbidity (myocardial infarction) - Coumarin derivative	XG boosting	Yes

Abbreviations: CT, Cardiothoracic; AUC, area under the curve; ECMO, Extracorporeal Membrane Oxygenation; Hgb, hemoglobin; ALB, albumin; RV, respiratory ventilation; GPR, Gaussian Process Regression; BSA, body surface area; CBP, cardiopulmonary bypass; RMSE, Root Mean Square Error; R², root square; MSBOS, Maximum Surgical Blood Ordering Schedule; PT, prothrombin time; INR, International Normalized Ratio; PTT, activated partial thrombin time; XG boosting, extreme gradient boosting.

*Most meaningful variables.

Table 3. Published Machine Learning Models for Orthopedic Surgery

Study	Characteristics	Number of cases		Type of validation	Prediction accuracy	Significant variables found	Type of ML used	Interpretable design
		Training	Validation					
Chen et al,23 2023	Multicenter. 7 hospitals in China. Orthopedic surgery.	47,684	11,921	Internal	AUC: 0.831	- Operation type* - Age* - RBC count - Preoperative erythropoietin - ALB - PTT - BMI	CatBoost	No
Zhou et al,34 2024	Single center. China. Hip fracture surgery.	2,228	99	Internal: 557 External: 122	AUC: 0.887 AUC: 0.834	- Type of surgery* - Duration of surgery* - Hyponatremia* - Preoperative anemia* - Age* - Types of anesthesia - Stroke - Wait time for surgery - ASA physical status - Hypertension - Sex	RF	Yes
Zang et al,35 2024	Single center. China. Hip fracture surgery.	2,431	730	Internal	AUC: 0.85	- Operation time* - Preoperative HgB* - Femoral head Necrosis - ASA physical status - Osteoarthritis - THA - Anemia - Autotransfusion - Fibrinogen - ALB	Ridge classifier	Yes
Zhu et al,30 2024	Multicenter center. 3 hospitals in China. THA for femoral neck fracture.	829	NP	Internal External	c-statistic: 0.98 c-statistic: 0.93	- IBL* - Preoperative HgB* - Operation time* - Preoperative ALB - BMI - Anticoagulant history - TXA use	LR	Yes

Abbreviations: AUC, area under the curve; RBC, red blood cell; ALB, albumin; PTT, activated partial thrombin time; BMI, body mass index; ASA, American Society of Anesthesiologist; RF, random forest; HgB, hemoglobin; THA, total hip arthroplasty; NP, not published; IBL, intraoperative blood loss; TXA, tranexamic acid; LR, logistic regression.
*Most meaningful variables.

ML model outperforms TRACK and TRUST in predicting transfusion risk. While these traditional risk scores incorporate similar variables – age, weight, sex, HgB/HCT levels, and history of prior surgery – they were developed using data from populations with higher baseline HgB levels than those in Brazil. This discrepancy underscores the limitations of generalized risk scores and highlights ML's ability to provide tailored predictions.¹⁸ Other models have been designed to enhance prediction accuracy by integrating clinical decision tools with dynamic patient data.

Hur et al. introduced the pMSBOS-TS model, integrating the MSBOS with patient-specific clinical and laboratory data to enhance transfusion predictions for thoracic surgery.⁹ The model shows superior predictive accuracy compared to MSBOS alone, reducing unnecessary T&S orders by one-third. Notably, it predicts transfusion likelihood and estimates the number of RBC units needed. The variables with the highest predictive impact include a high MSBOS score and low preoperative HCT. To improve transparency, a clinical decision support system is incorporated, explaining the rationale behind predictions. However, a significant limitation of the model is its reliance on single-center data, reducing its generalizability.⁹

Machine learning models for orthopedic surgeries

In orthopedic surgery, ML models have identified novel transfusion risk factors. Besides the proven predictors—advanced age, low HgB, anticoagulant use, and low BMI—a multicenter ML model also identified low albumin (ALB) levels and prolonged activated partial thromboplastin time (APTT) as significant risk factors for postoperative RBC transfusion.²³ Preoperative ALB levels reflect nutritional status and liver function, with low values suggesting malnutrition and anemia, both of which increase transfusion risk. Similarly, prolonged APTT indicates impaired coagulation, heightening intraoperative and postoperative bleeding risk and, consequently, transfusion likelihood.²³ These findings have

prompted more focused investigations into transfusion risks within specific orthopedic procedures such as hip surgeries.

Two independent research teams developed ML models for transfusion risk prediction in hip surgery. Zhou et al. used single-center data to identify preoperative variables linked to intraoperative RBC transfusion risk in unilateral hip fracture surgery.³⁴ This model indicates that internal fixation surgery, prolonged operative duration, and hyponatremia significantly increase intraoperative transfusion risk. The model underwent external validation, achieving excellent predictive performance. Zang et al. developed a similar ML model focused on perioperative transfusion prediction for hip surgery patients.³⁵ This model extends the predictive timeframe to 72 hours postoperatively but lacks external validation, limiting its broader applicability. Building on these efforts, other models have been designed for other types of orthopedic procedures, such as THA, to further refine transfusion risk predictions.³⁰

Zhu et al. 2024 developed a ML predictive model for patients undergoing THA following femoral neck fractures.³⁰ After selecting key features and processing data, researchers identified 7 independent risk factors for blood transfusion: BMI, surgical duration, intraoperative blood loss, anticoagulant history, tranexamic acid usage, preoperative HgB, and preoperative ALB. Although the model performs well in internal validation, its predictive accuracy declines slightly when evaluated with external datasets.³⁰ The reduced effectiveness highlights the challenges of generalizability in ML models. However, despite these limitations, the model is still a valuable tool for assessing transfusion risk, supporting clinical decision-making, and improving perioperative blood management.

Discussion

The integration of machine learning into transfusion risk prediction represents a significant advancement in perioperative care. While traditional risk scores offer acceptable

accuracy, they often lack adaptability and fail to capture the complexity of individual patient profiles. Recent studies highlight the limitations of these conventional methods and emphasize the need for more precise, personalized tools. ML models stand out for their ability to process large datasets and detect complex, non-linear relationships among variables, something traditional models struggle with. These models have shown accuracy across a range of surgical specialties, offering a more dynamic and data-driven approach to predicting transfusion needs. Their flexibility and scalability make them a valuable asset in enhancing clinical decision-making and improving patient outcomes.

A central advantage of ML-based models is the ability to continuously learn and evolve as new data becomes available. This dynamic learning ability allows models to improve over time, unlike traditional static scoring systems, which often rely on fixed parameters and outdated population data.¹⁸ Furthermore, ML approaches enable personalization and customization of predictions based on patient-specific variables, such as comorbidities, medications, intraoperative variables, and laboratory trends, providing a more tailored approach to transfusion planning. Similarly, including hospital and procedure-specific historical data in the building of the algorithm improve prediction accuracy.^{3,9,23,34} Such individualized predictions lead to better resource allocation, reduce blood product wastage, and improve patient outcomes. The customization process is also affected by the chosen ML method, which differs based on the size and complexity of the data.

The types of ML methods used differ. As expected, ensemble methods, such as CatBoost, random forest, and GB demonstrate a higher prediction accuracy in larger data sets.^{9,14,23,34} Simpler methods, such as LR, ridge classifier, and Gaussian regression, are valuable with smaller data sets.^{18,30,32,33,35} While model selection plays a key role in prediction accuracy, other factors such as study design

and dataset origin introduce limitations and potential biases.

There are persistent limitations and biases evident in the use of ML methods and evaluations. Most studies were conducted in single-center environments with retrospective designs, limiting the generalizability of the findings.^{18,32-35} External validation is notably lacking, and the models developed in one healthcare setting may not perform equally well in another due to differences in surgical practices, data documentation, and patient demographics. The predictive models demonstrate robust performance on internal validation data; however, those with external validation show a decrease in accuracy when applied to external datasets.^{3,30,34} This shows that due to the level of personalization, the algorithms benefit from incorporating local data in the learning process to achieve an excellent prediction. One example of a model that embraces the localized learning approach is the S-PATH model, which has undergone external validation across multiple hospital settings.^{3,14} This model allows the input of local hospital and procedure-specific transfusion risks. S-PATH prediction accuracy is higher using local datasets than when using transfusion risks from a national dataset.³ However, the model's performance still varied among different hospitals, showing that unmeasurable contributors, such as local transfusion culture, continue to affect the rate of perioperative transfusions.

Another notable limitation in ML models is related to the quality and quantity of the data. Small sample sizes, inconsistent definitions of transfusion triggers, and heterogeneous data preprocessing methods further complicate comparative analysis and model reproducibility. A common question in ML is how much training data is needed for the model to work well.³¹ This is important because the amount of data can significantly impact the accuracy and reliability of the model. Finding the right balance between data quantity and quality is essential. It is widely accepted that using larger training datasets (typically more than 1,000 instances) tends to result in more

accurate models.³¹ With larger datasets, ML algorithms are better equipped to identify complex patterns and relationships, improving overall model performance. Notably, the ML model that demonstrated lower performance was trained with fewer than 400 cases.¹⁸

Additionally, during model validation, careful consideration must be given to the selection of input variables. Omitting critical clinical data, such as coagulation parameters or medication use, limits the impact of the model's ability to accurately predict transfusion needs.^{30,34,35} However, even when data quality and quantity is addressed, translating ML predictive models into routine clinical practice introduces a new set of logistical challenges.

Successful integration of ML into healthcare requires a robust information technology infrastructure to support data integration from various sources and real-time processing, introducing a logistical limitation to many institutions. Furthermore, data used for model training must be accurate, standardized, and well-organized. This is a significant hurdle in many hospitals where electronic health records are fragmented or inconsistently maintained.^{8,33} Additionally, the "black-box" nature of some ML algorithms pose challenges for clinical acceptance, as transparency and interpretability are vital in medical decision-making.^{23,32,33} When authors lack transparency when publishing ML model selection or performance metrics, they are limiting the interpretability and replicability. Transparency in the ML model helps clinicians trust the prediction, as they can see and make sense of the associated risk. Organizational readiness, including provider's trust and continuous education, is crucial for adoption.

In addition to technical and organizational limitations, potential biases were also observed. Selection bias is a concern in retrospective studies where the dataset may not represent the broader surgical population.³⁶ Additionally, publication bias may favor studies that report higher model performance, while negative or inconclusive findings are less

likely to be published. The exclusion of patient cases due to missing data, electronic unavailability of important variables that influence transfusions risk, and authors not reporting how missing data was handled, introduces the possibility of information bias.

Although the development of innovative technologies, practices, and care models mark significant milestones in healthcare, technical innovation is only part of the equation. Successfully replicating and expanding healthcare innovation from one study or setting to a different context is neither straightforward nor guaranteed. Future research should address these limitations through multicenter, prospective studies with diverse populations and standardized data collection. There is a clear need for external validation of existing models, as well as the development of models that incorporate explainable components to ease clinical adoption. Additionally, the inclusion of blood products beyond RBCs is necessary when evaluating perioperative transfusion risk to support comprehensive product availability. Finally, the integration of ML models within electronic health record systems should be explored, with emphasis on assessing the real-world impact on transfusion practices, cost savings, and patient outcomes.

Conclusion

Effective prediction of transfusion needs is essential for optimizing blood inventory management, ensuring that limited blood products are allocated efficiently, while minimizing the risk of shortages and reducing unnecessary waste. ML offers a transformative approach to predicting perioperative transfusion risk. By leveraging large, diverse datasets and identifying complex, non-linear patterns, ML models can significantly enhance clinical decision-making, improve blood utilization, and lead to better patient outcomes across a wide range of surgical specialties.

However, integrating these models into clinical practice presents several challenges. Performance variability across institutions, limited external validation, retrospective

study designs, and inconsistent data quality all hinder widespread clinical adoption. Operational obstacles such as fragmented electronic health records, lack of standardized input variables, and the "black box" nature of some ML algorithms further complicate implementation. The effectiveness of ML models depends on access to high-quality, structured data and the ability for continuous validation and updates to ensure ongoing accuracy.

While the path to clinical integration of ML in perioperative transfusion prediction is

complex, the potential benefits make it a worthwhile endeavor. With thoughtful design, rigorous validation, and interdisciplinary collaboration, ML has the capacity to redefine how health care approaches transfusion planning. ML models outperform perioperative transfusion guidelines by using real-time data, recognizing complex patterns, and personalizing decisions, leading to more accurate and efficient blood utilization in surgical patients.

References

1. Gammon RR, Coberly E, Dubey R, Jindal A, Nalezinski S, Varisco JL. Patient blood management - it is about transfusing blood appropriately. *Ann Blood*. 2022;7:21. doi: 10.21037/aob-21-70
2. Jadwin DF, Fenderson PG, Friedman MT, et al. Determination of Unnecessary Blood Transfusion by Comprehensive 15-Hospital Record Review. *Jt Comm J Qual Patient Saf*. 2023;49(1):42-52. doi:10.1016/j.jcjq.2022.10.006
3. Lou SS, Liu Y, Cohen ME, Ko CY, Hall BL, Kannampallil T. National Multi-Institutional Validation of a Surgical Transfusion Risk Prediction Model. *J Am Coll Surg*. 2024;238(1):99-105. doi:10.1097/XCS.0000000000000874
4. Meier JM, Tschoellitsch T. Artificial Intelligence and Machine Learning in Patient Blood Management: A Scoping Review. *Anesth Analg*. 2022;135(3):524-531. doi:10.1213/ANE.0000000000006047
5. Lou SS, Dewey MM, Bollini ML, et al. Reducing perioperative red blood cell unit issue orders, returns, and waste using failure modes and effects analysis. *Transfusion*. 2023;63(4):755-762. doi:10.1111/trf.17275
6. Khalifa M, Elhassan E, Ibrahim F. Maximum surgical blood ordering schedule for elective surgical procedures in Omdurman teaching hospital, Sudan. *BMC Surg*. 2024;24(1):173. Published 2024 Jun 1. doi:10.1186/s12893-024-02458-4
7. Ahmed A. Pro: Can We Use Artificial Intelligence-Derived Algorithms to Guide Patient Blood Management Decision-Making? *J Cardiothorac Vasc Anesth*. 2023 Oct;37(10):2141-2144. doi: 10.1053/j.jvca.2023.05.045. Epub 2023 Jun 3. PMID: 37365072.
8. An Q, Rahman S, Zhou J, Kang JJ. A Comprehensive Review on Machine Learning in Healthcare Industry: Classification, Restrictions, Opportunities and Challenges. *Sensors (Basel)*. 2023;23(9):4178. Published 2023 Apr 22. doi:10.3390/s23094178
9. Hur S, Yoo J, Min JY, et al. Development, validation, and usability evaluation of machine learning algorithms for predicting personalized red blood cell demand among thoracic surgery patients. *Int J Med Inform*. 2024;191:105543. doi:10.1016/j.ijmedinf.2024.105543
10. Cohn CS, Delaney M, Johnson ST, Katz LM. *Technical Manual*. 20th ed. AABB; 2020.
11. World Health Organization. *Global status report on blood safety and availability 2016*. Geneva. 2017. <https://www.who.int>. Accessed on 02/22/2025
12. Pan Z, Charoenkwan K. Prediction Models for Perioperative Blood Transfusion in Patients Undergoing Gynecologic Surgery: A Systematic Review. *Diagnostics (Basel)*. 2024;14(18):2018. Published 2024 Sep 12. doi:10.3390/diagnostics14182018

13. Guduri PR, Shastry S, Raturi M, Shenoy A. Surgical blood ordering schedule for better inventory management: An experience from a tertiary care transfusion center. *Med J Armed Forces India*. 2022;78(3):283-290. doi:10.1016/j.mjafi.2020.07.004
14. Lou SS, Liu H, Lu C, Wildes TS, Hall BL, Kannampallil T. Personalized Surgical Transfusion Risk Prediction Using Machine Learning to Guide Preoperative Type and Screen Orders. *Anesthesiology*. 2022;137(1):55-66. doi:10.1097/ALN.0000000000004139
15. Carson JL, Stanworth SJ, Guyatt G, et al. Red Blood Cell Transfusion: 2023 AABB International Guidelines. *JAMA*. 2023;330(19):1892-1902. doi:10.1001/jama.2023.12914
16. Friedman BA, Oberman HA, Chadwick AR, Kingdon KI. The maximum surgical blood order schedule and surgical blood use in the United States. *Transfusion*. 1976;16(4):380-387. doi:10.1046/j.1537-2995.1976.16476247063.x
17. Morberg PCW, Ringdal KG, Espinosa A, Lindholm E. Excessive use of preoperative blood type and antibody screening: A retrospective observational study conducted in a hospital in Norway. *Acta Anaesthesiol Scand*. 2024;68(10):1327-1337. doi:10.1111/aas.14493
18. Cunha CBCD, Lima TA, Ferraz DLM, et al. Predicting the Need for Blood Transfusions in Cardiac Surgery: A Comparison between Machine Learning Algorithms and Established Risk Scores in the Brazilian Population. *Braz J Cardiovasc Surg*. 2024;39(2):e20230212. Published 2024 Mar 1. doi:10.21470/1678-9741-2023-0212
19. Gupta N, Visagie M, Kajstura TJ, et al. Reducing preoperative blood orders and costs for radical prostatectomy. *J Comp Eff Res*. 2020;9(3):219-226. doi:10.2217/cer-2019-0126
20. Verret M, Lalu M, Sessler DI, et al. Perioperative Transfusion Practices in Adults Having Noncardiac Surgery. *Transfus Med Rev*. 2024;38(3):150839. doi:10.1016/j.tmr.2024.150839
21. Irving A, Harris A, Petrie D, et al. Can clinical guidelines reduce variation in transfusion practice? A pre-post study of blood transfusions during cardiac surgery. *Vox Sang*. 2025;120(1):47-54. doi:10.1111/vox.13751
22. Marwaha JS, Beaulieu-Jones BR, Berrigan M, et al. Quantifying the Prognostic Value of Preoperative Surgeon Intuition: Comparing Surgeon Intuition and Clinical Risk Prediction as Derived from the American College of Surgeons NSQIP Risk Calculator. *J Am Coll Surg*. 2023;236(6):1093-1103. doi:10.1097/XCS.0000000000000658
23. Chen Y, Cai X, Cao Z, et al. Prediction of red blood cell transfusion after orthopedic surgery using an interpretable machine learning framework. *Front Surg*. 2023;10:1047558. Published 2023 Mar 2. doi:10.3389/fsurg.2023.1047558
24. Van den Eynde R, Vrancken A, Foubert R, et al. Prognostic models for prediction of perioperative allogeneic red blood cell transfusion in adult cardiac surgery: A systematic review and meta-analysis. *Transfusion*. Published online December 26, 2024. doi:10.1111/trf.18108
25. Madhu Krishna NR, Nagaraja PS, Singh NG, et al. Evaluation of risk scores in predicting perioperative blood transfusions in adult cardiac surgery. *Ann Card Anaesth*. 2019;22(1):73-78. doi:10.4103/aca.ACA_18_18
26. Ranucci M, Castelveccchio S, Frigiola A, Scolletta S, Giomarelli P, Biagioli B. Predicting transfusions in cardiac surgery: the easier, the better: the Transfusion Risk and Clinical Knowledge score. *Vox Sang*. 2009;96(4):324-332. doi:10.1111/j.1423-0410.2009.01160.x
27. Alghamdi AA, Davis A, Brister S, Corey P, Logan A. Development and validation of Transfusion Risk Understanding Scoring Tool (TRUST) to stratify cardiac surgery

- patients according to their blood transfusion needs. *Transfusion*. 2006;46(7):1120-1129. doi:10.1111/j.1537-2995.2006.00860.x
28. Grandone E, Tiscia GL, Ostuni A, Marongiu F, Barcellona D. Navigating anemia and anticoagulation in elderly patients undergoing orthopedic surgery: strategies for preventing complications and implementing treatments. *Blood Transfus*. 2024;22(5):450-458. doi:10.2450/BloodTransfus.640
 29. Pempe C, Werdehausen R, Pieroh P, et al. Predictors for blood loss and transfusion frequency to guide blood saving programs in primary knee- and hip-arthroplasty. *Sci Rep*. 2021;11(1):4386. Published 2021 Feb 23. doi:10.1038/s41598-021-82779-z
 30. Zhu J, Xu C, Jiang Y, et al. Development and Validation of a Machine Learning Algorithm to Predict the Risk of Blood Transfusion after Total Hip Replacement in Patients with Femoral Neck Fractures: A Multicenter Retrospective Cohort Study. *Orthop Surg*. 2024;16(8):2066-2080. doi:10.1111/os.14160
 31. Srinivas TA, Thanmai BT, Donald AD, et al. Training data alchemy: balancing quality and quantity in machine learning training. *J Network Security Data Mining*. 2023;6(3):7-10. doi:10.5281/zenodo.8138725.
 32. Park I, Park JH, Yoon J, et al. Assessment of machine learning classifiers for predicting intraoperative blood transfusion in non-cardiac surgery. *Transfus Clin Biol*. 2025;32(1):1-8. doi:10.1016/j.tracli.2024.10.006
 33. Wang Z, Zhe S, Zimmerman J, et al. Development and validation of a machine learning method to predict intraoperative red blood cell transfusions in cardiothoracic surgery. *Sci Rep*. 2022;12(1):1355. Published 2022 Jan 25. doi:10.1038/s41598-022-05445-y
 34. Zhou Y, Wang S, Wu Z, et al. An explainable and supervised machine learning model for prediction of red blood cell transfusion in patients during hip fracture surgery. *BMC Anesthesiol*. 2024;24(1):467. Published 2024 Dec 19. doi:10.1186/s12871-024-02832-y
 35. Zang H, Hu A, Xu X, Ren H, Xu L. Development of machine learning models to predict perioperative blood transfusion in hip surgery. *BMC Med Inform Decis Mak*. 2024;24(1):158. Published 2024 Jun 5. doi:10.1186/s12911-024-02555-7
 36. Howlett B, Rogo EJ, Shelton TG. *Evidence-Based Practice for Health Professionals*. 2nd ed. Jones & Bartlett Learning; 2021

