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RESEARCH

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Mapping the landscape of machine learning models used for predicting transfusions in surgical procedures: a scoping review

Olivier Duranteau^{1,2,3*}, Florian Blanchard⁴, Benjamin Popoff^{5,6}, Faridi S. van Etten-Jamaludin⁷, Turgay Tuna^{1,2} and Benedikt Preckel⁸

Abstract

Massive transfusion of blood products poses challenges in determining the need for transfusion and the appropriate volume of blood products. This review explores the use of machine learning (ML) models to predict transfusion risk during surgical procedure, focusing on the methodology, variables, and software employed to predict transfusion. This scoping review investigates the development and current state of machine learning models for predicting transfusion risk during surgical procedure, aiming to inform physicians about the field's progress and potential directions.

The review was conducted using the databases Cochrane, Embase, and PubMed. The search included keywords related to blood transfusion, statistical models, and surgical procedures. Peer-reviewed articles were included, while literature reviews, case reports, and non-human studies were excluded.

A total of 40 studies met the inclusion criteria. The most frequently studied biological variables included haemoglobin, platelet count, international normalized ratio (INR), activated partial thromboplastin time (aPTT), fibrinogen, creatinine, white blood cells, and albumin. Clinical variables of importance included age, sex, surgery type, blood pressure, weight, surgery duration, american society of anesthesiology (ASA) status, blood loss, and body mass index (BMI). The software employed varied, with Python, R, SPSS, and SAS being the most commonly used. Logistic regression was the predominant methodology used in 20 studies.

Our scoping review highlights the need for improved reporting and transparency in methodology, variables, and software used. Future research should focus on providing detailed descriptions and open access to codes of respective models, promoting reproducibility, and enhancing the clinical relevance of transfusion risk prediction models.

Keywords Transfusion, Machine learning, Prediction, Massive haemorrhage

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Introduction

Significance

Massive transfusion of blood products presents several challenges, such as identifying the need for transfusion as early as possible, and administering the most appropriate volume of blood products [1]. Clinical, paraclinical and biological criteria are used to assess the need for transfusion. In patients with major haemorrhage, haemodynamic, biological and haemostatic status changes rapidly and over a wide range [2], especially during surgery. This is the major reason why recommendations advocate transfusion ratios that allow for rapid action [3–6].

Background

During surgical procedures, standard haemostasis parameters are often inappropriate in massive transfusion situations due to the time required for blood sample transport and analysis. In addition, the results of these analyses primarily characterise disorders of the endogenous or exogenous coagulation pathways but don't allow the identification of specific factor deficits for targeted treatment. The advent of off-site monitoring tools such as thromboelastography (TEG[®], Haemonetics Corporation[®], Boston, USA) or thromboelastometry (ROTEM[®], Werfen[®], Barcelona, Spain) represents a significant improvement in perioperative bleeding management [7]. However, the longer turnaround times (10–20 min) and extensive training required for analysis and interpretation of results may limit their use in case of massive haemorrhage [8]. Both standard tests and off-site monitoring provide only a snapshot of the patient's haemostatic status at a given time and in the case of massive haemorrhage, making interpretation of test results potentially obsolete by the time results are available. The development of machine learning (ML) or deep learning may provide a solution for improved guidance in the practice of massive transfusion [9, 10].

The term “machine learning” describes the algorithms used to find patterns in large amounts of data and to learn from these data [11]. However, the implementation of ML also faces several challenges, such as data retrieval volume, data reliability, clinical relevance, and staff training in ML and deep learning techniques [12].

Rationale

Numerous studies have attempted to model clinician intuition in transfusion practice to determine the optimal time to initiate blood transfusion [1, 9]. These studies often use ML to build models, but only a small proportion of them provide sufficient detail of their models to allow easy replication.

Aim and objectives

This scoping review examines the development and current state of machine learning models for predicting transfusion risk during surgery, with the aim of informing clinicians about the progress and potential directions of the fields. To achieve this aim, a comprehensive review of currently published models was undertaken, describing the variables, software and methodology used.

Materials and methods

The protocol of this review is available on request from the corresponding author. The literature review and research protocol were submitted to the figshare[®] register and approved under the reference “Skye”. Prisma and Moose checklists were followed [13, 14].

Sources of information

The databases analysed included the cochrane central register of controlled trials (CENTRAL), Cochrane systematic reviews, Embase/Ovid, and PubMed. The time period covered was from inception to 1 April 2022. There were no language restriction. Articles in languages other than French or English were translated with DeepL Translator[®] (DeepL[®] SE, Cologne, Germany).

Search strategy

Data extraction was conducted using the following keywords:

“Blood Transfusion” OR blood product transfusion* OR red blood cell transfusion* OR red blood cells transfusion* OR RBC transfusion* OR RBCs transfusion* OR blood cell transfusion* OR blood cells transfusion* OR packed cell transfusion* OR packed cells transfusion* or packed red blood cell* OR packed red cell* OR erythrocyte concentrate*.

OR fresh frozen plasma transfusion* OR plasma transfusion* OR FFP transfusion* OR lyophilized plasma transfusion* OR “Plasma” OR fresh frozen plasma*

OR thrombocyte transfusion* OR platelet transfusion* OR fibrinogen OR “Fibrinogen”

OR massive transfusion*

AND

“Models, Statistical” OR “Artificial Intelligence” OR artificial intelligence OR machine learning

AND

“Cardiac Surgical Procedures” OR cardiac surgery OR heart surgery

OR “Surgical Procedures, Operative” OR “Traumatology” OR trauma surgery

OR surgery

Eligibility criteria

Only peer-reviewed articles were included. All articles matching the specified keywords (transfusion prediction

during surgery) were included. Literature reviews, case reports, case series and studies on non-human subjects were excluded. After a thorough full-text review, articles that did not describe the design of a mathematical model but only defined variables for transfusion risk assessment were also excluded.

Selection process

Two reviewers independently screened the retrieved abstracts using the Agency for Healthcare Research and Quality systematic review data repository (SRDR+) software.

The authors screened the titles and abstracts of the search results. Two authors selected manuscripts based on their relevance to the study topic and eliminated articles with mismatched keywords. These two authors were blinded to each other's results. In the event of disagreement after the blind was lifted, a third, more experienced author made the final selection. During the data collection process, the two authors concerned excluded articles whose full text did not meet the study objectives.

Data collection process

Two additional authors, also blinded to each other, analysed all articles, and collected data using the same software. Due to the specific purpose of the study and the nature of the studies reviewed, suggested checklists such as CARE 2013 could not be used [15]. Therefore, prior to article analysis, all authors identified a list of 10 items to be completed with data from the articles. After each reviewer had analysed two articles, a meeting was held to determine the relevance of the items. At this stage, three items were added, resulting in a total of 13 items to be completed for each retrieved and included reference.

Data collected

In each article the following information was collected by the two authors.

- Country.
- Conducted in academic hospital
- Multicentre authors
- Study design
- Number of patients
- Inclusion and exclusion criteria
- Variables collected (biological and clinical)
- Software and statistics used
- Model description
- Validation (description and methodology)
- Code description.

Assessment of risk of bias in the review process

To minimize bias, the recommendations of the Joanna Briggs Institute were followed [16]. The three reviewers performed unbiased analyses according to the objectives described in the checklist above and were completely blinded to each other.

Software used: description

Currently, there are only a few software tools for ML in healthcare. However, a distinction must be made between a programming language (used by several software programs) and a software program (owned by a single company with proprietary functionality). The most important software and programming languages are described below.

Python® (Python Software Foundation)

Programming language (mainly used by the Anaconda® software), often used with packages (programming overlays that allow certain functions to be used directly without manual programming; this implies that all parameters have default values that can be modified if necessary).

R® (R Core Team)

Programming language (mainly used with R Studio® software), all actions must be manually coded.

SPSS® (IBM® Corp, Arming, NY, USA)

Software that allows direct modelling by simply specifying modalities, no coding required.

SAS® (SAS Institute)

Programming language and associated software. Allows modelling to be done directly by simply specifying modalities, with minimal coding required.

Model building: description

The development of a ML model is based on statistical concepts, the most important of which are described in Table 1.

Results

Study selection

The search identified 1,329 records, with 154 duplicates found, resulting in 1,175 articles for review. After title and abstract screening, 109 articles met the eligibility criteria and underwent full analysis and data extraction by reviewers. After detailed reading of the full articles, a further 68 manuscripts were excluded because they did not meet the objective of the predefined search, but only described variables to be studied to determine transfusion risk. A flowchart of the search results is shown in Fig. 1.

Table 1 Model construction description

| Logistic regression | Used to study the relationships between a set of categorical variables X_i and a categorical variable Y . It is used to predict the probability of an event by optimising the regression coefficients |
|-------------------------------|--|
| Decision tree | non-parametric supervised training algorithm used for both classification and regression tasks. It has a hierarchical, tree-like structure |
| Random forest | a composition of several decision trees trained independently on subsets of the training data set (bagging method). Each tree produces an estimate, and the combination of the results generates the final prediction, resulting in reduced variance |
| Neuronal network | a method that learns to process data in a manner inspired by the human brain. It is a type of process that uses nodes, or neurons, that are interconnected in a multi-layered structure |
| Support Vector Machine (SVM): | A set of supervised learning techniques designed to solve discrimination and regression problems. SVMs are a generalisation of linear classifiers |
| Linear Regression | a linear relationship is established between a dependent variable and one or more explanatory variables |
| K-Nearest Neighbour: | a non-parametric supervised training classifier that uses proximity to make classifications or predictions about a single data point's clustering |
| Nomogram | a graphical calculation tool consisting of graduated curves between which a ruler is placed |
| XG Boost algorithm | Combination of multiple weak decision trees to create a powerful predictive model. |
| Gaussian Naïve Bayes | Simple and efficient classifier that assumes independence between features |
| Adaboost | Boosting algorithm that changes the weights of data points to focus on harder-to-learn ones |
| Gradient boosting machine | General boosting technique that uses a gradient descent approach to improve model performance iteratively. |
| Maximum likelihood | Statistical method for estimating the parameters of a model that maximizes the probability of observing the data |
| Restricted Boltzmann machine | Type of neural network used for dimensionality reduction and feature learning. |
| Gaussian process | Probabilistic model that uses Gaussian distributions to make predictions and quantify uncertainty |
| Mann-Whitney U Test | Non-parametric test used to compare the medians of two unpaired samples |
| Elastic net | Regularization technique that combines L1 and L2 penalties to improve model performance and reduce overfitting |

Study characteristics

Forty studies were finally included [17–56] (Table 2). Supplementary Table 1 describes the number of patients included per study, the inclusion periods, and the inclusion and exclusion criteria of each study. The type of surgery at inclusion is described in Table 3. Only 5 studies clearly defined their research outcomes [37, 42, 43, 49, 54] (Supplementary Table 2), 28 performed risk estimation and calculation [17, 18, 20, 22, 26, 27, 29, 30, 32, 34, 36, 38–41, 43–51, 53–56].

Variables used in included studies

Logistic regression was used as a variable selection method in a total of 20 studies [18, 19, 21, 23–27, 29, 31, 33–35, 39–41, 43–48, 51, 52, 54–56] and was not well described in the other studies [17, 20, 22, 28, 30, 32, 36–38, 42, 49, 50, 53] (Supplementary Table 3).

The most commonly studied biological variables were haemoglobin, platelet count, INR, aPTT, fibrinogen and creatinine, white blood cells (WBC) and albumin. Haemoglobin was the only biological parameter used in a total of 10 trials [20, 21, 27, 35, 41–43, 47, 52, 56]. Only 4 studies included TEG or ROTEM as monitored parameters [22, 23, 29, 46] (Table 4, Supplementary Table 2).

Regarding demographic data, the most commonly analysed variables were age, sex, weight, body mass index (BMI) and body surface area (BSA), medical history (American Society of Anesthesiology (ASA) physical status, presence of diabetes mellitus or chronic obstructive pulmonary disease). Surgical characteristics were often

analysed (duration, type of surgery, blood loss, intraoperative blood pressure and identification of the surgeon). Eleven studies didn't report patient sex and age [23, 27, 29, 30, 32, 37, 45–48, 56] (Table 3, Supplementary Tables 1 & 2).

Software used and model created

The software used for ML (Table 1) was not described in 6 studies [17, 18, 24, 30, 37, 53]. Eight studies used R language [21, 23, 25, 27, 32, 42, 44, 54] or SPSS software [21, 23, 26, 27, 39–41, 45], seven studies used SAS software [19, 33, 34, 43, 47, 50, 54] or Python language [20, 36, 38, 39, 49, 52, 55], (Supplementary Table 3).

Thirty-one studies didn't publish the code of their work [21–25, 28, 30–45, 47–54], 8 published it [17, 18, 20, 26, 27, 29, 55, 56] and 1 described a pseudo code [46] (Table 1). The publication of the exact and precise code allows an identical reproduction of the protocol and thus a possible additional external verification by the reader. This is an add value for the manuscript.

More than half (23) of the studies produced a model based on logistic regression [17–19, 21, 31–35, 40–45, 47, 48, 50–53, 55, 56], 6 produced a neural network (4,8,14,16,20,21), 5 studies used a nomogram [23, 25–27, 44]. Ten studies defined multiples methods for the model used [17, 20, 24, 26, 30, 32, 36, 37, 49, 54] (Fig. 2, Supplementary Table 3).

Model validation was mostly internal with data splitting in 16 studies [17–32, 38, 39, 42, 43, 46, 47, 49, 50, 52,

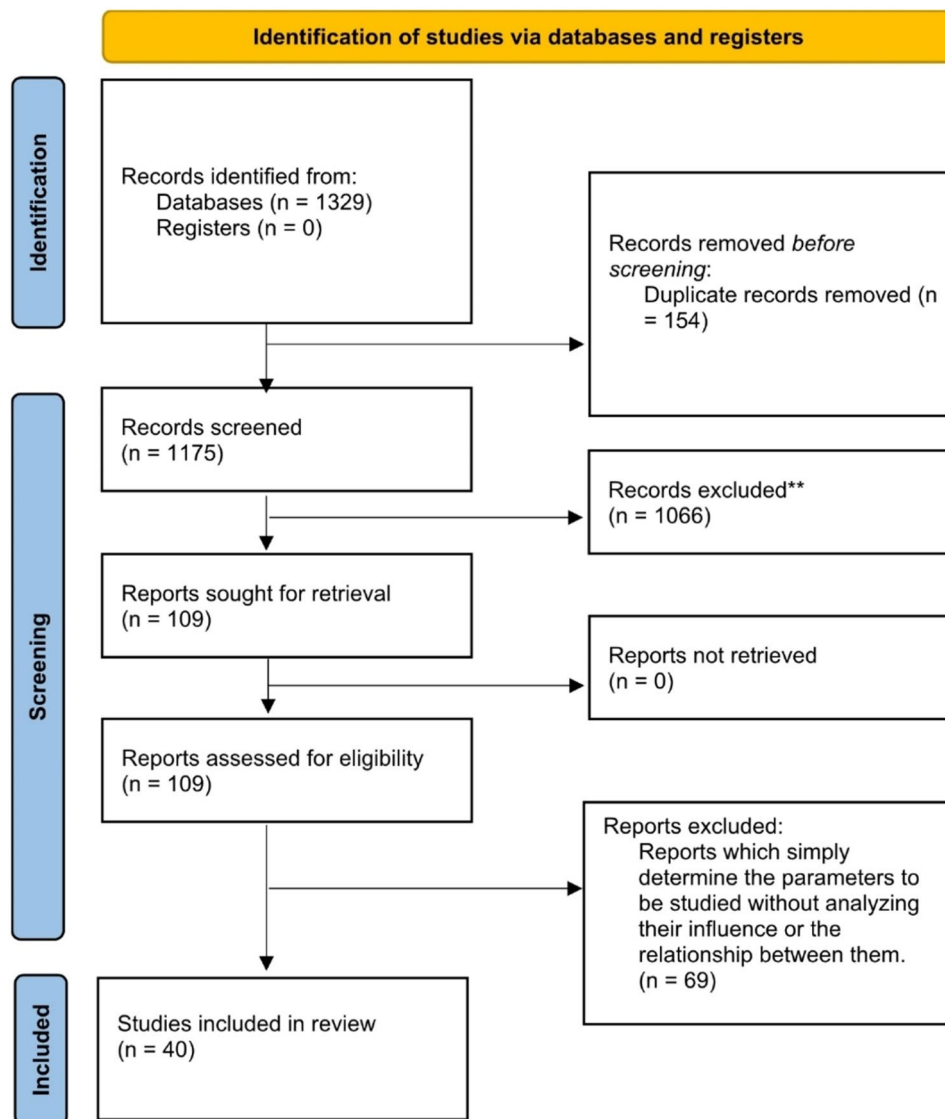


Fig. 1 Flow of studies through the scoping review

54, 56] and reality checking in 19 others (Supplementary Table 3). There was no validation process in 4 studies [34, 48, 51, 53] and only one study used external validation [55].

Management of missing data

Eleven studies used a data imputation procedure [17, 22, 24, 28, 32, 37, 38, 42, 44, 54] while 8 others excluded patients with missing data [17, 23–25, 29, 31, 34, 36, 41, 43, 46, 49, 52, 54, 56] (Supplementary Table 2). The remaining studies simply did not describe how they handled missing data [18–21, 26, 27, 30, 33, 35, 40, 45, 47, 48, 50, 51, 53, 55].

Discussion

In this scoping review, we analysed the existing literature on modelling the indication for transfusion, highlighting the diversity of methods and tools that have been developed. To the best of our knowledge, this is the first review on this topic that looks at the details of the ML models that have been developed to predict the need for transfusion.

Based on the reviewed articles, the most commonly used biological variables are : haemoglobin, platelets, haematocrit, creatinine, INR, aPTT, albumin, WBC, PT, TEG and fibrinogen. The most commonly used clinical variables are : age, sex, surgery type, blood pressure, weight, duration of surgery, ASA physical status, blood loss, BMI and diabetes.

Table 2 General data on studies

| Study N° | Reference | Publication Date | Country | Academic hospital | Multi-centre authors | Study design | Funding sources | Registered | Ethics committee | Software used | code access |
|----------|-----------|------------------|---------|-------------------|----------------------|---------------|-----------------|-----------------|------------------|-----------------------|---------------------|
| 1 | [12] | 2021 | China | Yes | Yes | Retrospective | public grant | clinical trials | Local | non de-scribed | open (git hub etc.) |
| 2 | [13] | 1989 | USA | Yes | No | Retrospective | no information | no information | no information | non de-scribed | open (git hub etc.) |
| 3 | [14] | 2010 | USA | Yes | No | Retrospective | none | none | Local | SAS | blinded |
| 4 | [15] | 2019 | China | Yes | Yes | Retrospective | none | none | Local | Python | open (git hub etc.) |
| 5 | [16] | 2020 | USA | Yes | Yes | Retrospective | none | none | none | R SPSS | blinded |
| 6 | [17] | 2021 | USA | Yes | No | Retrospective | none | none | National | Google Cloud Platform | blinded |
| 7 | [18] | 2021 | China | Yes | No | Retrospective | public grant | none | Local | R SPSS | blinded |
| 8 | [19] | 2022 | USA | Yes | Yes | Retrospective | private grant | none | Local | non de-scribed | blinded |
| 9 | [20] | 2021 | China | Yes | No | Retrospective | private grant | none | Local | R | blinded |
| 10 | [21] | 2021 | China | Yes | Yes | Retrospective | none | none | Local | SPSS | open (git hub etc.) |
| 11 | [22] | 2020 | China | Yes | No | Retrospective | none | none | Local | R SPSS | open (git hub etc.) |
| 12 | [23] | 2017 | Austria | Yes | Yes | Retrospective | public grant | none | none | MAT-LAB | blinded |
| 13 | [24] | 2021 | UK | Yes | Yes | Retrospective | public grant | none | National | age-naRisk | open (git hub etc.) |
| 14 | [25] | 2015 | USA | Yes | No | Retrospective | public grant | none | none | non de-scribed | blinded |
| 15 | [26] | 2003 | USA | Yes | No | Retrospective | public grant | none | none | S-plus | blinded |
| 16 | [27] | 2017 | USA | Yes | Yes | Retrospective | none | none | none | R | blinded |
| 17 | [28] | 2004 | Canada | Yes | No | Retrospective | none | none | none | SAS | blinded |
| 18 | [29] | 2017 | USA | No | No | Retrospective | none | none | none | SAS | blinded |
| 19 | [30] | 2009 | France | Yes | No | Retrospective | none | none | Local | Excel JMP | blinded |
| 20 | [31] | 2020 | USA | Yes | Yes | Prospective | none | none | National | Python | blinded |
| 21 | [32] | 2021 | China | Yes | No | Retrospective | public grant | none | Local | non de-scribed | blinded |
| 22 | [33] | 2021 | China | Yes | Yes | Retrospective | public grant | none | Local | Python | blinded |
| 23 | [34] | 2021 | China | Yes | Yes | Retrospective | public grant | none | Local | Python SPSS | blinded |
| 24 | [35] | 1996 | USA | Yes | No | Retrospective | no information | no information | no information | SPSS BMDP | blinded |
| 25 | [36] | 1995 | USA | Yes | No | Prospective | no information | no information | no information | SPSS BMDP | blinded |
| 26 | [37] | 2017 | USA | No | No | Retrospective | none | none | local | R | blinded |
| 27 | [38] | 2001 | Canada | Yes | Yes | Prospective | public grant | none | Local | SAS | blinded |

Table 2 (continued)

| Study N° | Reference | Publication Date | Country | Academic hospital | Multi-centre authors | Study design | Funding sources | Registered | Ethics committee | Software used | code access |
|----------|-----------|------------------|-------------|-------------------|----------------------|---------------|-----------------|------------|------------------|-------------------|---------------------|
| 28 | [39] | 2016 | USA | Yes | Yes | Retrospective | none | none | Local | R Stata | blinded |
| 29 | [40] | 1997 | Canada | Yes | No | Retrospective | public grant | none | no information | SPSS | blinded |
| 30 | [41] | 2015 | USA | Yes | No | Prospective | none | none | none | JustNN | pseudo code |
| 31 | [42] | 2004 | Canada | Yes | No | Retrospective | none | none | Local | SAS | blinded |
| 32 | [43] | 2001 | Japan | Yes | No | Prospective | none | none | none | Stat-View | blinded |
| 33 | [44] | 2021 | China | Yes | No | Retrospective | public grant | ChiCTR | Local | Python | blinded |
| 34 | [45] | 2013 | Israel | Yes | No | Retrospective | none | none | Local | SAS | blinded |
| 35 | [46] | 2017 | Italy | Yes | No | Retrospective | none | none | none | Stata | blinded |
| 36 | [47] | 2021 | Egypt | Yes | No | Retrospective | none | none | National | Python | blinded |
| 37 | [48] | 2014 | Brazil | Yes | No | Retrospective | none | none | none | non described | blinded |
| 38 | [49] | 2018 | USA | Yes | Yes | Retrospective | none | none | none | R SAS Julia | blinded |
| 39 | [50] | 2020 | South Korea | Yes | No | Retrospective | none | none | Local | Python | open (git hub etc.) |
| 40 | [51] | 2003 | USA | Yes | No | Retrospective | none | none | Local | Stata | open (git hub etc.) |

Table 3 Classification of type of surgery at patient inclusion

| Type of surgery at patient inclusion | Number of studies |
|--------------------------------------|-------------------|
| Cardiothoracic surgery | 12 |
| Orthopaedic surgery | 12 |
| Traumatology | 4 |
| Surgery | 4 |
| Cranio-facial surgery | 3 |
| digestive surgery | 2 |
| Liver surgery | 1 |
| Gynaecologic surgery | 1 |
| Obstetrical surgery | 1 |

Most of the trials analysed used the same biological or demographic variables. For example, haemoglobin is an important variable in the assessment of blood product transfusion. It should be remembered that the transfusion of red blood cells, which mainly modifies this parameter, is both an agent (correction of haemostasis disorders) and a measure of haemorrhagic shock (measurement of the amount of red blood cells transfused). The lack of studies analysing TEG or ROTEM point-of-care devices is surprising given their increasing use in clinical contexts of massive haemorrhage. The frequent analysis of white blood cells and albumin is noteworthy. The evolution of white blood cells can be rapid, but this evolution can also be modified by several other causes. As for albumin, its evolution is very slow compared to

the changes in patient's clinical condition. Its inclusion in several studies suggests its potential value in predicting transfusion needs during massive transfusion. The demographic parameters used were also mostly classical (age, sex, weight, height, etc.). Furthermore, this scoping does not answer the question of the influence of the experience of the treating physician on patient morbidity and mortality, which has been reported in several articles [57, 58].

Regarding the software used, the distribution observed in this review reflects current practices in ML, with a clear dominance of the four main tools (Python, R, SAS, and SPSS). Similarly, the models developed are in line with current advances in the field, with logistic regression modelling and the emergence of more innovative techniques (e.g. random forest, neural network, decision tree) being prominent. Logistic regression is easier to implement and understand, but the binary results limit detailed analysis. So far, no machine learning model has shown significant superiority over the others [59]. Similarly, the use of simple logistic or linear regression appears to provide as much information and relevance as much more complex models [60]. The relevance of using complex models should therefore be discussed. The principle of Occam's razor can be applied to this issue: "*Entities are not to be multiplied without necessity.*"

Table 4 Variables studied, ranked according to the number of studies in which the variable was studied

| Biological variables | Number of studies | Clinical variables | Number of studies |
|----------------------|-------------------|--------------------|-------------------|
| Haemoglobin | 31 | Age | 28 |
| Platelets | 16 | Sex | 21 |
| Haematocrit | 14 | Surgery Type | 18 |
| Creatinine | 14 | Blood pressure | 14 |
| INR | 12 | Weight | 14 |
| APTT | 9 | Surgery duration | 14 |
| Albumin | 8 | ASA Status | 13 |
| White blood Cells | 7 | Blood loss | 12 |
| PT | 6 | BMI | 11 |
| TEG | 5 | Diabetes | 10 |
| Fibrinogen | 5 | BSA | 7 |
| ASAT | 4 | Height | 6 |
| RBC | 4 | COPD | 6 |
| Thrombin time | 4 | Surgeon | 6 |
| PaCO2 | 3 | LVEF | 5 |
| Urea | 3 | Charlson Index | 3 |
| MCV | 3 | RR | 2 |
| PaO2 | 3 | | |
| Base deficit | 2 | | |
| Lactate | 2 | | |

INR: International Normalized Ratio, APTT: Activated Partial Thromboplastin Time, PT: Prothrombin Time, TEG: Thromboelastography, ASAT: Aspartate Aminotransferase, RBC: Red Blood Cell, PaCO2: Partial Pressure of Carbon Dioxide in Arterial Blood, MCV: Mean Corpuscular Volume, PaO2: Partial Pressure of Oxygen in Arterial Blood, ASA Status: American Society of Anesthesiologists Physical Status, BMI: Body Mass Index, BSA: Body Surface Area, COPD: Chronic Obstructive Pulmonary Disease, LVEF: Left Ventricular Ejection Fraction, RR: Respiratory Rate

If we were to propose a list of factors that would predict the need for massive transfusion, we would make the following list. For clinical variables: Age, sex, type of surgery, weight, duration of surgery, ASA status, blood loss. For biological variables: Haemoglobin, platelets,

creatinine, INR, APTT. The model to be used would be logistic regression.

The studies analysed have several limitations. The first limitation is the non-publication of the model which severely limits the external validity of the publications. Publication of the model would increase the transparency and thus the quality of the study by avoiding possible bias and allowing the reader to reproduce the study. Secondly, only five studies clearly described their primary objectives, and most lacked clarity, making it difficult to fully accept the results. In addition, it was often difficult to understand the methodology used to select data for analysis, as data collection, cleaning and missing data management were rarely described. Finally, very few studies published their a priori research protocol in a registry database and none published the exact research methodology, raising concerns about potential data trawling (i.e. including as much data as possible with as many models as possible and then seeing which set is most relevant).

This literature review is innovative in that it examines not only the variables collected but also the ML methodology used to predict transfusion in massive transfusion scenarios. It is important to understand the machine learning processes involved in model design and variable selection methodology. This allows the clinician to critique the results reported by the authors, just as the analysis of a correlation coefficient can be used to moderate the results of a prediction study.

In summary, numerous models are described, some of which apply to the same populations with the same analysed values. The question arises as to the clinical relevance of these models, as most of the articles do not suggest any change in practice that should (or could) be made locally. Only two manuscripts lead to the production of easily accessible online resources.

Further work in the field of haemorrhagic risk prediction in surgery would be to describe the implementation

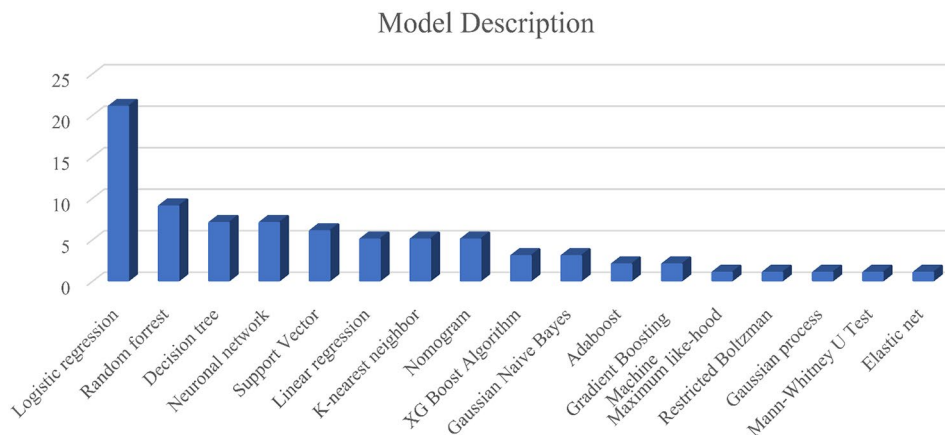


Fig. 2 Model described and constructed in the different studies. Model type on the x-axis in descending order of the number of studies with this inclusion criterion. Each model is described in Table 1

Table 5 Proposition of check-list for prediction model publication

| Country | |
|--|--|
| Type of institution support (academic, commercial) | |
| Origin of authors | |
| Study design | |
| Population | Number of patients |
| Population | Inclusion criteria |
| Population | Exclusion criteria |
| Population | Inclusion period |
| Income | Biological values |
| Income | Clinical values |
| Income | Method of selection |
| Model | Software used |
| Model | Statistics used to assess the model |
| Model | Model description |
| Model | Validation methods (internal and external) |
| Model | Code description, available for reproduction |

of these models prospectively as an aid to prescribing and then to look at the effects on mortality, morbidity and the amount of transfusion given. A proposed checklist of the various items of information that should be included in the publication of a manuscript describing the design of a machine learning model is given in Table 5. It lists the various items that were evaluated during the course of this review.

Conclusion

This scoping review provided a descriptive overview of ML modelling of transfusion risk conception during surgery. We found that most studies investigated similar biological and clinical variables and used comparable methodologies. Unfortunately, the majority of articles inadequately described their methodology making reproducibility difficult. Future publications should include an appendix detailing the various methodological aspects of the ML methods used, thus promoting transparency and facilitating replication.

Glossary of terms

| | |
|------|---------------------------------------|
| ML | Machine learning |
| INR | International normalized ratio |
| aPTT | activated partial thromboplastin time |
| ASA | American society of anesthesiology |
| BMI | Body mass index |
| WBC | White blood cells |

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

Supplementary Material 4

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Author contributions

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Data availability

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References

- McQuilten ZK, Crighton G, Brunskill S, Morison JK, Richter TH, Waters N, et al. Optimal dose, timing and ratio of blood products in massive transfusion: results from a systematic review. *Transfus Med Rev.* 2018;32:6–15. <https://doi.org/10.1016/j.tmr.2017.06.003>.
- Muirhead B, Weiss ADH. Massive hemorrhage and transfusion in the operating room. *Can J Anesth/J Can Anesth.* 2017;64:962–78. <https://doi.org/10.1007/s12630-017-0925-x>.
- Spahn DR, Bouillon B, Cerny V, Duranteau J, Filipescu D, Hunt BJ, et al. The European guideline on management of major bleeding and coagulopathy following trauma: fifth edition. *Crit Care.* 2019;23:98. <https://doi.org/10.1186/s13054-019-2347-3>.
- Muñoz M, Stensballe J, Ducloy-Bouthors A-S, Bonnet M-P, De Robertis E, Fornet I, et al. Patient blood management in obstetrics: prevention and treatment of postpartum haemorrhage. A NATA consensus statement. *Blood Transfus.* 2019;17:112–36. <https://doi.org/10.2450/2019.0245-18>.
- Vlaar APJ, Dionne JC, de Bruin S, Wijnberge M, Raasveldt SJ, van Baarle FEHP, et al. Transfusion strategies in bleeding critically ill adults: a clinical practice guideline from the European Society of Intensive Care Medicine. *Intensive Care Med.* 2021;47:1368–92. <https://doi.org/10.1007/s00134-021-06531-x>.
- Holcomb JB, Tilley BC, Baraniuk S, Fox EE, Wade CE, Podbielski JM, et al. Transfusion of plasma, platelets, and red blood cells in a 1:1:1 vs a 1:1:2 ratio and mortality in patients with severe trauma: the PROPPR randomized clinical trial. *JAMA.* 2015;313:471–82. <https://doi.org/10.1001/jama.2015.12>.
- Sakai T. Comparison between thromboelastography and thromboelastometry. *Minerva Anesthesiol.* 2019;85:1346–56. <https://doi.org/10.23736/S0375-9393.19.13687-5>.
- Da Luz LT, Nascimento B, Shankarakutty AK, Rizoli S, Adhikari NK. Effect of thromboelastography (TEG®) and rotational thromboelastometry (ROTEM®) on diagnosis of coagulopathy, transfusion guidance and mortality in trauma: descriptive systematic review. *Crit Care.* 2014;18:518. <https://doi.org/10.1186/s13054-014-0518-9>.

9. Mitterecker A, Hofmann A, Trentino KM, Lloyd A, Leahy MF, Schwarzbauer K, et al. Machine learning–based prediction of transfusion. *Transfusion*. 2020;60:1977–86. <https://doi.org/10.1111/trf.15935>.
10. Meier JM, Tschoellitsch T. Artificial Intelligence and Machine Learning in Patient Blood Management: a scoping review. *Anesth Analgesia*. 2022;135:524. <https://doi.org/10.1213/ANE.0000000000006047>.
11. What is machine learning? MIT Technology Review. n.d. <https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/> (accessed February 23, 2024).
12. Connor CW. Artificial Intelligence and Machine Learning in Anesthesiology. *Anesthesiology*. 2019;131:1346–59. <https://doi.org/10.1097/ALN.0000000000002694>.
13. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*. 2021;372:n71. <https://doi.org/10.1136/bmj.n71>.
14. Brooke BS, Schwartz TA, Pawlik TM. MOOSE Reporting guidelines for Meta-analyses of Observational studies. *JAMA Surg*. 2021;156:787–8. <https://doi.org/10.1001/jamasurg.2021.0522>.
15. CARE Checklist. CARE Case Report Guidelines n.d. <https://www.care-statement.org/checklist> (accessed February 23, 2024).
16. Katrak P, Bialocerkowski AE, Massy-Westropp N, Kumar VS, Grimmer KA. A systematic review of the content of critical appraisal tools. *BMC Med Res Methodol*. 2004;4:22. <https://doi.org/10.1186/1471-2288-4-22>.
17. Huang X, Wang Y, Chen B, Huang Y, Wang X, Chen L, et al. Ability of a machine learning Algorithm to Predict the need for Perioperative Red Blood cells transfusion in pelvic fracture patients: a Multicenter Cohort Study in China. *Front Med (Lausanne)*. 2021;8:694733. <https://doi.org/10.3389/fmed.2021.694733>.
18. Bilfinger TV, Conti VR. Blood conservation in coronary artery bypass surgery: prediction with assistance of a computer model. *Thorac Cardiovasc Surg*. 1989;37:365–8.
19. Welsby I, Crow J, Bandarenko N, Lapps G, Phillips-Bute B, Stafford-Smith M. A clinical prediction tool to estimate the number of units of red blood cells needed in primary elective coronary artery bypass surgery. *Transfusion*. 2010;50(11):2337–43. <https://doi.org/10.1111/j.1537-2995.2010.02711.x>.
20. Yao Y, Cifuentes J, Zheng B, Yan M. Computer algorithm can match physicians' decisions about blood transfusions. *J*. 2019;17:340.
21. Raman T, Vasquez-Montes D, Varlotta C, Passias PG, Errico TJ. Decision tree-based modelling for identification of predictors of blood loss and transfusion requirement after adult spinal deformity surgery. *Int J Spine Surg*. 2020;14:87–95.
22. Shahi N, Shahi AK, Phillips R, Shirek G, Bensard D, Moulton SL. Decision-making in pediatric blunt solid organ injury: a deep learning approach to predict massive transfusion, need for operative management, and mortality risk. *J Pediatr Surg*. 2021;56:379–84.
23. Shen R, Wang X, Lu Z. Development and Internal Validation of Model Predicting postoperative blood loss risk among children with pulmonary atresia undergoing cardiopulmonary bypass. *Pediatr Cardiol*. 2021;42:47–58.
24. Wang Z, Zhe S, Zimmerman J, Morrissey C, Tonna JE, Sharma V, et al. Development and validation of a machine learning method to predict intraoperative red blood cell transfusions in cardiothoracic surgery. *Sci*. 2022;12:1355.
25. Huang H, Cao M. Development and validation of a nomogram to predict intraoperative blood transfusion for gastric cancer surgery. *Transfus Med*. 2021;31:250–61.
26. Dong S, Li W, Tang ZR, Wang H, Pei H, Yuan B. Development and validation of a novel predictive model and web calculator for evaluating transfusion risk after spinal fusion for spinal tuberculosis: a retrospective cohort study. *BMC Musculoskelet Disord*. 2021;22.
27. Wang JQ, Chen LY, Jiang BJ, Zhao YM. Development of a Nomogram for Predicting Blood Transfusion Risk after Hemiarthroplasty for femoral Neck fractures in Elderly patients. *Med Sci Monit*. 2020;26:e920255.
28. Hayn D, Kreiner K, Ebner H, Kastner P, Rzepnik N, Rzepka A, et al. Development of Multivariable models to predict and Benchmark transfusion in elective surgery supporting patient blood management. *Appl Clin Inf*. 2017;8:617–31.
29. Perkins ZB, Yet B, Marsden M, Glasgow S, Marsh W, Davenport R, et al. Early identification of trauma-induced Coagulopathy: Development and Validation of a multivariable risk prediction model. *Ann Surg*. 2021;274:e1119–28.
30. Ngufor C, Murphree D, Upadhyaya S, Madde N, Kor D, Pathak J. Effects of plasma transfusion on perioperative bleeding complications: a Machine Learning Approach. *Stud Health Technol Inf*. 2015;216:721–5.
31. Covin R, O'Brien M, Grunwald G, Brimhall B, Sethi G, Walczak S, et al. Factors affecting transfusion of fresh frozen plasma, platelets, and red blood cells during elective coronary artery bypass graft surgery. *Arch Pathol Lab Med*. 2003;127:415–23.
32. De Pasquale M, Moss TJ, Cerutti S, Calland JF, Lake DE, Moorman JR, et al. Hemorrhage Prediction models in Surgical Intensive Care: Bedside Monitoring Data adds information to Lab Values. *IEEE j*. 2017;21:1703–10.
33. Arora RC, Legare JF, Buth KJ, Sullivan JA, Hirsch GM. Identifying patients at risk of intraoperative and postoperative transfusion in isolated CABG: toward selective conservation strategies. *Ann Thorac Surg*. 2004;78:1547–54.
34. Slover J, Lavery JA, Schwarzkopf R, Iorio R, Bosco J, Gold HT. Incidence and risk factors for blood transfusion in total joint arthroplasty: analysis of a Statewide Database. *J Arthroplasty*. 2017;32:2684–e26871.
35. Lenoir B, Merckx P, Paugam-Burtz C, Dauzac C, Agostini MM, Guigui P, et al. Individual probability of allogeneic erythrocyte transfusion in elective spine surgery: the predictive model of transfusion in spine surgery. *Anesthesiology*. 2009;110:1050–60.
36. Jalali A, Lonsdale H, Zamora LV, Ahumada L, Nguyen ATH, Rehman M et al. Machine learning Applied to Registry Data: development of a patient-specific prediction model for blood transfusion requirements during Craniofacial surgery using the Pediatric Craniofacial Perioperative Registry dataset. *Anesth Analg*. 2020;160–71.
37. Feng Y, Xu Z, Sun X, Wang D, Yu Y. Machine learning for predicting preoperative red blood cell demand. *Transfus Med*. 2021;31:262–70.
38. Liu LP, Zhao QY, Wu J, Luo YW, Dong H, Chen ZW, et al. Machine learning for the prediction of red blood cell transfusion in patients during or after liver transplantation surgery. *Front Med (Lausanne)*. 2021;8:632210.
39. Liu S, Zhou R, Xia XQ, Ren H, Wang LY, Sang RR, et al. Machine learning models to predict red blood cell transfusion in patients undergoing mitral valve surgery. *Ann*. 2021;9:530.
40. Magovern JA, Sakert T, Benckert DH, Burkholder JA, Liebler GA, Magovern GJ, Sr, et al. A model for predicting transfusion after coronary artery bypass grafting. *Ann Thorac Surg*. 1996;61:27–32.
41. Weber RS. A model for predicting transfusion requirements in head and neck surgery. *Laryngoscope*. 1995;105:1–17.
42. Stanhiser J, Chagin K, Jelovsek JE. A model to predict risk of blood transfusion after gynecologic surgery. *Am J Obstet Gynecol*. 2017;216:e5061–50614.
43. Karkouti K, Cohen MM, McCluskey SA, Sher GD. A multivariable model for predicting the need for blood transfusion in patients undergoing first-time elective coronary bypass graft surgery. *Transfusion*. 2001;41:1193–203.
44. Kim Y, Bagante F, Gani F, Ejaz A, Xu L, Wasey JO, et al. Nomogram to predict perioperative blood transfusion for hepatopancreaticobiliary and colorectal surgery. *Br J Surg*. 2016;103:1173–83.
45. Larocque BJ, Gilbert K, Brien WF. A point score system for predicting the likelihood of blood transfusion after hip or knee arthroplasty. *Transfusion*. 1997;37:463–7.
46. Huang RSP, Nedelcu E, Bai Y, Wahed A, Klein K, Tint H, et al. Post-operative bleeding risk stratification in cardiac pulmonary bypass patients using artificial neural network. *Ann Clin Lab Sci*. 2015;45:181–6.
47. Rashid S, Shah M, Chow AK, O'Connor PJ, Finegan BA. Predicting allogeneic blood transfusion use in total joint arthroplasty. *Anesth Analg*. 2004;99:1239–44.
48. Isomatsu Y, Tsukui H, Hoshino S, Nishiya Y. Predicting blood transfusion factors in coronary artery bypass surgery. *Jpn J Thorac Cardiovasc Surg*. 2001;49:438–42.
49. Huang Z, Martin J, Huang Q, Ma J, Pei F, Huang C. Predicting postoperative transfusion in elective total HIP and knee arthroplasty: comparison of different machine learning models of a case-control study. *Int J Surg*. 2021;96.
50. Kadar A, Chechik O, Steinberg E, Reider E, Sternheim A. Predicting the need for blood transfusion in patients with hip fractures. *Int Orthop*. 2013;37:693–700.
51. Pieri M, Nardelli P, De Luca M, Landoni G, Frassoni S, Melissano G, et al. Predicting the need for intra-operative large volume blood transfusions during Thoraco-abdominal aortic aneurysm repair. *Eur J Vasc Endovasc Surg*. 2017;53:347–53.
52. Shazly SA, Hortu I, Shih JC, Melekoglu R, Fan S, Ahmed FUA, et al. Prediction of clinical outcomes in women with placenta accreta spectrum using machine learning models: an international multicenter study. *Journal of Maternal Fetal and Neonatal Medicine*; 2021.
53. Cristante AF, Borges PA, Barbosa AR, Letaif OB, Marcon RM, Barros Filho TE. Predictive factors for perioperative blood transfusion in surgeries for correction of idiopathic, neuromuscular or congenital scoliosis. *Clinics*. 2014;69:672–6.

54. Durand WM, DePasse JM, Daniels AH. Predictive Modeling for Blood Transfusion After Adult Spinal Deformity Surgery: A Tree-Based Machine Learning Approach. *Spine*. 2018;43:1058–66.
55. Jo C, Ko S, Shin WC, Han HS, Lee MC, Ko T, et al. Transfusion after total knee arthroplasty can be predicted using the machine learning algorithm. *Knee Surg Sports Traumatol Arthrosc*. 2020;28:1757–64.
56. Krupp NL, Weinstein G, Chalian A, Berlin JA, Wolf P, Weber RS. Validation of a transfusion prediction model in head and neck cancer surgery. *Arch Otolaryngol Head Neck Surg*. 2003;129:1297–302.
57. McAteer JP, LaRiviere CA, Drugas GT, Abdullah F, Oldham KT, Goldin AB. Influence of surgeon experience, hospital volume, and specialty designation on outcomes in pediatric surgery: a systematic review. *JAMA Pediatr*. 2013;167:468–75. <https://doi.org/10.1001/jamapediatrics.2013.25>.
58. Canal C, Kaserer A, Ciritsis B, Simmen H-P, Neuhaus V, Pape H-C. Is there an influence of Surgeon's experience on the clinical course in patients with a proximal femoral fracture? *J Surg Educ*. 2018;75:1566–74. <https://doi.org/10.1016/j.jsurg.2018.04.010>.
59. Krishnan R, Rajpurkar P, Topol EJ. Self-supervised learning in medicine and healthcare. *Nat Biomed Eng*. 2022;6:1346–52. <https://doi.org/10.1038/s41551-022-00914-1>.
60. Christodoulou E, Ma J, Collins GS, Steyerberg EW, Verbakel JY, Calster BV. A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. *J Clin Epidemiol*. 2019;110:12–22. <https://doi.org/10.1016/j.jclinepi.2019.02.004>.

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