ORIGINAL RESEARCH Open access

Machine Learning Model for Forecasting Daily Blood Product Demand in Tertiary Hospitals Using Surgical Schedules, Trauma Admissions, Transfusion History, Oncology Treatment Plans, and Inventory Depletion Patterns

Andreas Müller[1*], Stefan Weber[1], Julia Hoffmann[2], Lukas Schneider[1], Tobias Klein[2]

Abstract

Blood products are critical hospital resources with demand shaped by elective surgery, trauma, oncology treatment, and ongoing transfusion dependence. Volatility in daily use can create simultaneous risks of shortage and expiry-related wastage. Current inventory management often relies on par-level reordering and manual review of limited indicators. Such approaches may not anticipate daily demand shifts arising from multiple clinical drivers at the same time. This article develops a conceptual predictive model for forecasting daily blood product demand in tertiary hospitals. The model integrates surgical schedules, trauma admission patterns, transfusion history, oncology treatment plans, and inventory depletion data. The proposed approach uses time-series regression or gradient-boosted tree modelling trained on historical transfusion and hospital operations data. The model would output expected demand by blood product type for the next 24 hours. Conceptually, the model would provide a daily product-specific demand forecast with uncertainty bounds. It could flag days of expected high use driven by complex surgical lists, trauma activity, or planned oncology transfusion support. The model could support proactive, data-driven blood inventory management. It may help reduce emergency ordering, improve preparedness, and limit avoidable wastage.

Keywords Machine learning, Predictive analytics, Blood product demand forecasting, Transfusion medicine, Hospital inventory, Surgical schedules

*Correspondence:
Andreas Müller
andreas.mueller@gmail.com
[1] Department of Digital Health Systems and Analytics, Faculty of Medicine, Heidelberg University, Heidelberg, Germany
[2] Department of Clinical Informatics Engineering, Faculty of Engineering, Technical University of Munich, Munich, Germany

Introduction

Blood product inventory management in tertiary hospitals requires a balance between immediate availability for life-threatening haemorrhage and avoidance of expiry-related wastage. Red blood cells, platelets, plasma, and cryoprecipitate differ in storage constraints, clinical indications, and replenishment patterns, making daily demand difficult to manage with a single static rule. Recent work in blood supply forecasting and inventory optimisation has shown that modelling demand and ordering jointly could support more reliable transfusion service planning [1, 2]. This dual challenge is especially acute in hospitals with high surgical, trauma, and oncology workloads, where predictable and unpredictable demand streams converge.

Current forecasting in many blood banks depends heavily on recent average use, par-level thresholds, and manual awareness of major clinical activity. These methods may underrepresent specific predictors such as cardiac surgery schedules, transplant activity, orthopaedic cases, and chemotherapy-related cytopenias. Studies of perioperative transfusion prediction show that procedure characteristics, patient condition, and operative context can provide clinically meaningful signals before blood products are issued [3-9]. A daily forecasting model could therefore move beyond average usage by incorporating planned care pathways into operational demand planning.

Electronic health record integration creates an opportunity to extract real-time clinical schedules, patient-level transfusion history, and blood bank workflow data for predictive modelling. Machine learning methods have already been applied to platelet demand, intraoperative transfusion, and blood inventory ordering, suggesting that structured hospital data can support more adaptive forecasting [10-13]. Patient-specific transfusion histories are particularly relevant for chronically transfused haematology and oncology patients, while issue and reservation logs can describe how demand materialises operationally [11, 14]. These data streams could allow a model to forecast not only expected use but also the clinical reasons behind expected demand.

This article proposes a machine learning model that produces a daily blood product demand forecast by synthesising planned and historical clinical predictors alongside inventory behaviour. The model is conceptual rather than experimental, and it is intended to describe how transfusion service data could be organised, processed, interpreted, and deployed. Prior research on blood demand forecasting, perioperative transfusion prediction, trauma transfusion modelling, and chemotherapy-induced cytopenias provides the rationale for integrating these predictors into a single hospital-level architecture. The central premise is that daily demand is best treated as a product-specific operational outcome shaped by both scheduled care and stochastic emergency use.

Table 1 conceptualises how distinct categories of demand drivers contribute differently to predictability, modelling strategy, and operational decision-making.

Table 1. Comparative Structure of Planned, Stochastic, and Recurrent Drivers of Blood Product Demand

Demand Driver Category	Core Data Sources	Temporal Predictability	Mechanistic Role in Demand Formation	Modelling Representation	Operational Implication
Planned Procedural Demand	Surgical schedules, procedure codes, preoperative labs	High (scheduled in advance)	Determines expected transfusion probability based on procedure type and patient condition	Deterministic aggregation with probabilistic weighting by procedure risk	Enables proactive cross-matching and pre-allocation of components
Recurrent Chronic Demand	Oncology treatment plans, transfusion history	Moderate to high (cycle-based but variable)	Reflects ongoing transfusion dependence due to cytopenia or marrow failure	Patient-level longitudinal features aggregated to daily demand signals	Supports anticipatory platelet and RBC inventory positioning
Stochastic Emergency Demand	Trauma admissions, ED activity, MTP activation logs	Low (unpredictable onset)	Introduces sudden high-volume demand variability	Probabilistic modelling with uncertainty distributions	Requires buffer stock and conservative inventory policies

Operational Feedback Demand	Inventory depletion rates, reservation logs, expiry patterns	Moderate (reactive but patterned)	Captures how demand materialises through workflow and stock movement	Time-series features reflecting velocity and deviation from baseline	Aligns forecast with real-time stock pressure and wastage risk
Hybrid Interaction Effects	Combined clinical and inventory signals	Variable	Interaction between planned and unplanned drivers amplifying demand peaks	Nonlinear interactions captured via machine learning models	Identifies surge days requiring escalation in ordering strategy

Background

Blood product usage patterns in tertiary hospitals

Blood product use in tertiary hospitals reflects a mixture of routine, urgent, and episodic clinical need across red blood cells, platelets, plasma, and cryoprecipitate. Red blood cell use is often associated with surgery, bleeding, anaemia, and critical illness, while platelet demand is strongly influenced by haematology-oncology care and procedural bleeding risk. Platelet ordering is particularly sensitive to short shelf life, changing clinical schedules, and patient-level thresholds, which makes it an important target for predictive inventory planning [10-13, 15-20]. Demand forecasting must therefore distinguish product type, clinical indication, and timing rather than treating all blood components as interchangeable units.

Surgical schedules as a demand predictor

Surgical schedules are a natural source of planned demand signals because procedure type, anticipated blood loss, preoperative haemoglobin, and institutional ordering protocols shape transfusion probability. Machine learning studies in perioperative settings suggest that structured preoperative and intraoperative data could help predict transfusion need across cardiac, orthopaedic, liver transplant, and general surgical populations [10-13, 21-23]. For a daily hospital demand model, surgical information would be aggregated from individual case-level predictors into a product-specific estimate for the next ordering cycle. This approach would allow blood banks to prepare for high-risk operating lists while preserving specialist review and manual override.

Trauma and emergency demand

Trauma demand differs from elective surgical demand because massive transfusion protocol activation can occur suddenly and may require rapid issue of multiple components. Predictive modelling of massive transfusion in trauma has explored how early clinical indicators and registry variables could identify patients likely to require high-volume blood support [24-26]. A hospital demand model could incorporate recent trauma admissions, emergency department activity, and activation patterns as probabilistic rather than fixed inputs. This would help express trauma demand as uncertainty around expected use rather than as a deterministic daily total.

Oncology transfusion dependence

Oncology and haematology services create recurring transfusion demand through chemotherapy-induced anaemia, thrombocytopenia, marrow failure, and supportive care protocols. Predictive models for chemotherapy-induced thrombocytopenia indicate that treatment regimen, patient characteristics, and disease context can inform expectations about future cytopenic risk [27-29]. In a blood demand forecasting model, oncology treatment calendars and transfusion history could identify patients likely to require scheduled platelet or red cell support. These features would make planned oncology demand visible to the blood bank before orders are placed.

Machine learning for inventory and demand forecasting in healthcare

Machine learning and time-series approaches have been applied to blood demand forecasting, platelet ordering, and supply-demand matching, offering a basis for integrated hospital inventory decision support. Prior studies have combined statistical modelling, machine learning, and inventory optimisation to connect demand forecasts with order quantities and stock management decisions [1, 2, 10, 21-23]. Broader predictive analytics in transfusion medicine also includes donor prediction, transfusion risk modelling, and red blood cell quality analytics, demonstrating the range of data-driven methods relevant to blood services [30, 31]. For hospital operations, the key design challenge is to translate forecasts into interpretable and auditable actions within existing transfusion workflows.

Model Development Overview

High-level predictive pipeline

The proposed predictive pipeline would ingest daily data from the surgical scheduling system, trauma registry, oncology electronic health record flowsheets, transfusion service logs, and blood bank inventory system. Each source would contribute time-stamped signals describing expected clinical activity, recent unplanned demand, patient-level transfusion dependence, and current stock movement. The model would then generate a product-specific forecast for the next 24 hours, aligned with blood bank ordering and reservation workflows [1, 2, 23]. This architecture treats demand forecasting as an operational process linking clinical activity to component availability rather than as a stand-alone statistical exercise.

Figure 1 illustrates the hierarchical architecture of the proposed predictive pipeline integrating clinical, operational, and inventory-derived signals into a unified daily blood product demand forecast.

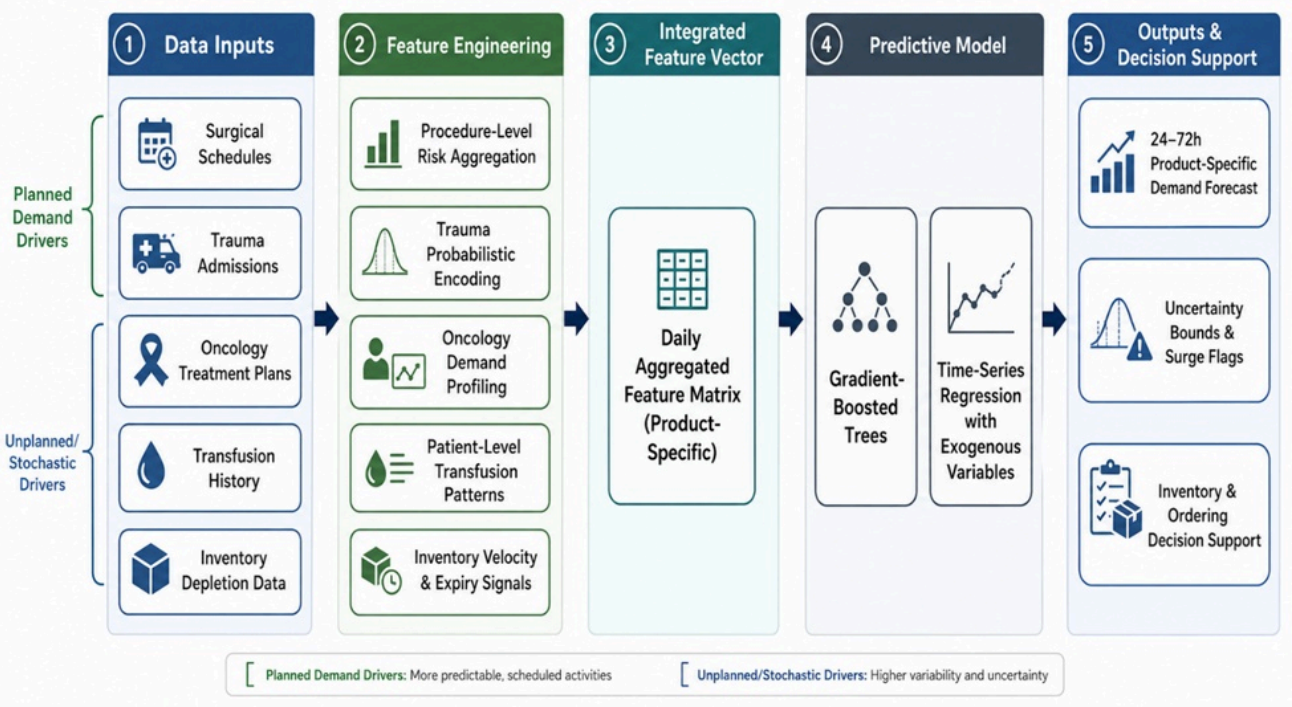


Figure 1. Hierarchical Predictive Pipeline for Daily Blood Product Demand Forecasting in Tertiary Hospitals

Core input features

Core input features would include the number and type of scheduled surgeries, estimated transfusion probability by procedure category, recent trauma admissions, active oncology patients with planned treatment or transfusion dates, historical transfusion behaviour per patient, and current inventory level by component. Surgical models indicate that procedure context and patient status can inform transfusion risk, while platelet demand models show the value of patient-specific features in forecasting component need [3-9, 15-20]. Trauma features would be represented through recent emergency activity and activation patterns rather than assumed fixed demand [24-26]. Inventory features would describe depletion behaviour, reservation pressure, and issue frequency to connect predicted clinical need with operational stock movement [1, 10].

Design principles

The model should operate on a daily cadence that matches blood bank ordering cycles while remaining flexible enough to refresh when key clinical schedules change. It should be robust to missing or delayed data, especially when elective surgery schedules are incomplete, oncology treatment dates are revised, or trauma activity changes rapidly. Interpretability is essential because transfusion service staff must understand why the model anticipates high demand and when manual override is appropriate [11-13, 23]. The design should also flag forecasted surge days so that blood bank managers can distinguish routine replenishment from days requiring conservative preparedness.

Data Sources and Feature Engineering

Surgical schedule feature extraction

Surgical schedule feature extraction would convert operating room lists into daily predictors, including procedure codes, surgical specialty, scheduled start time, expected blood loss category, and patient preoperative haemoglobin status. Procedure-specific transfusion models in cardiac, orthopaedic, transplant, liver, and general surgery suggest that such variables can be useful for anticipating perioperative blood use [3-9, 15-20]. These case-level predictors would be aggregated into expected daily demand signals for red blood cells, plasma, platelets, and cryoprecipitate. The resulting feature set would support proactive cross-match and reservation planning while preserving clinician review for high-risk cases.

Trauma, transfusion history, and oncology features

Trauma features would include emergency admissions, shock or activation indicators, and recent massive transfusion protocol activity, represented as probabilistic drivers of unplanned demand. Transfusion history features would summarise recurrent patient-level use, such as recent red cell or platelet support, chronic transfusion patterns, and proximity to prior component issue. Oncology features would be derived from treatment calendars, expected cytopenia timing, and supportive care plans, reflecting the predictable component of chemotherapy-associated transfusion need [14, 27-29]. Together, these predictors would allow the model to combine sudden emergency demand with recurring and planned transfusion dependence [24-26].

Inventory depletion pattern features

Inventory depletion features would describe current stock by product type and blood group, recent issue velocity, reservation pressure, near-expiry stock, and wastage risk. Prior work linking demand forecasting to inventory ordering shows that forecast outputs become more useful when they are connected to stock levels and replenishment decisions [1, 2, 10]. Seasonality, weekday effects, and recent deviations from expected use would help the model recognise operational patterns that are not fully explained by clinical schedules. These features would enable the forecast to represent not only expected clinical demand but also the pace at which available inventory is being consumed.

Predictive Analytics Architecture

Model choice and rationale

A gradient-boosted tree model or a time-series regression model with exogenous clinical regressors would be appropriate for this conceptual architecture. Gradient-boosted trees could capture nonlinear interactions among surgical case mix, oncology treatment activity, trauma admissions, and current inventory status, while time-series models could represent recurring temporal structure in daily component use. Prior transfusion and blood inventory studies support the relevance of machine learning, statistical forecasting, and integrated inventory optimisation for this type of structured hospital problem [1-3, 10, 21-23]. The selected model should prioritise interpretability, stability, and clinical plausibility rather than only statistical fit.

Input feature vector and preprocessing

The input feature vector would combine continuous variables such as recent depletion rates and expected surgical blood use with categorical variables such as product type, surgical specialty, blood group, and admission pathway. Continuous features could be standardised or transformed for model stability, while categorical features could be encoded so that product-specific patterns remain visible to the algorithm. Missing values from weekend schedules, delayed oncology updates, or incomplete emergency data would require explicit handling rather than silent exclusion, because these absences may themselves carry operational meaning [11, 21, 22]. Preprocessing should preserve auditability so that blood bank staff can trace how each forecast was generated from source data.

Output: daily demand forecast by product

The model would output daily demand forecasts by blood product type, with the option to express results as rounded unit expectations and prediction intervals for 24-, 48-, and 72-hour horizons. Product-specific outputs are important because red blood cells, platelets, plasma, and cryoprecipitate differ in storage duration, clinical urgency, and replenishment constraints. Forecasts could be displayed alongside recent use, scheduled high-risk activity, and current inventory position to support ordering decisions within transfusion service workflows [1, 10, 23]. The output should remain advisory, allowing transfusion medicine specialists to adjust decisions based on contextual information not captured in the model.

Handling Uncertainty and Surge Events

Modelling stochastic trauma demand

Trauma-related demand should be represented as a probabilistic component because emergency haemorrhage and massive transfusion activation cannot be scheduled in advance. Prior trauma prediction studies suggest that early clinical and admission signals could inform the likelihood of high-volume transfusion without eliminating uncertainty [24-26]. The model would therefore output a likely demand range rather than a single fixed estimate for trauma-driven use. This approach would help blood banks prepare conservatively while recognising that not every high-risk trauma signal becomes sustained component demand.

Surgical cancellation and schedule changes

Elective surgical demand can change when cases are added, delayed, cancelled, or converted to more complex procedures. A useful forecasting system would refresh when live operating room schedules change, allowing the predicted demand profile to adjust before products are cross-matched or reserved. Perioperative transfusion prediction studies indicate that procedure type, patient status, and operative context are relevant signals, so schedule updates should directly alter the forecast [3-9, 15-20]. In practice, the model would support repeated intra-day review rather than a single static morning estimate.

Flagging high-uncertainty forecasts

High-uncertainty forecasts should be flagged when multiple drivers are unstable, such as complex surgery lists, recent trauma admissions, or oncology patients with uncertain transfusion timing. Prediction intervals would be used conceptually to distinguish routine expected use from days requiring cautious inventory positioning. Prior work on blood demand forecasting and platelet ordering supports linking forecasts to operational decisions, but uncertainty must remain visible to avoid overconfidence [1, 10, 23]. A conservative alert could prompt blood bank managers to review stock, reservations, and supplier communication before demand materialises.

Model Interpretability and Blood Bank Integration

Explaining demand forecasts to blood bank staff

Interpretability is essential because transfusion service staff must understand why the model expects increased demand before acting on its recommendation. Explanation methods could identify whether forecasted platelet demand is driven by haematology patients, cardiac surgery, recent depletion, or a combination of these factors. Patient-level platelet modelling and broader transfusion analytics show that machine learning outputs are more useful when they can be connected to clinically recognisable drivers [11-13, 30]. Explanations would support trust, manual override, and governance by making the forecast auditable.

Integration with transfusion service dashboard

The model should be embedded in a transfusion service dashboard that displays predicted demand beside current stock, reservations, near-expiry units, and recommended order review. Such integration would connect forecasting to blood bank workflow rather than leaving predictions as isolated analytics outputs. Studies combining demand forecasting with inventory ordering show that operational value depends on linking predicted use to actionable replenishment decisions [1, 2, 10]. Colour-coded alerts could indicate when forecasted demand is expected to exceed available stock or when wastage risk requires redistribution.

Operational Deployment and Inventory Decision Support

Automated order recommendations

Automated order recommendations would translate the demand forecast into a proposed product order list that accounts for lead time, minimum stock thresholds, expected depletion, and component shelf life. The recommendation should remain subject to transfusion medicine specialist approval because clinical context and supplier constraints may not be fully captured in source data. Prior work on red blood cell ordering and platelet inventory management supports the conceptual value of connecting forecasts to ordering decisions [1, 2, 10]. The model would therefore function as decision support rather than autonomous inventory control.

Table 2 links forecast outputs and uncertainty signals to actionable blood bank decisions, emphasising the operational interpretation of predictive analytics.

Table 2. Analytical Mapping between Model Outputs, Uncertainty Signals, and Blood Bank Decision Actions

Model Output Type	Interpretation Layer	Uncertainty Characteristic	Decision Pathway	Risk if Ignored	Recommended Operational Response

Point Forecast (Mean Demand)	Baseline expected usage per product	Low to moderate	Routine inventory replenishment planning	Understocking or overstocking if misestimated	Align daily orders with expected depletion
Prediction Interval (Range)	Bounds of plausible demand variation	Explicitly quantified	Risk-aware inventory positioning	Overconfidence in point estimate leading to shortages	Maintain buffer stock proportional to interval width
Surge Flag (High-Demand Alert)	Identification of atypical demand drivers	High (multi-factor instability)	Escalated review and contingency planning	Failure to prepare for peak demand events	Increase stock thresholds and review supplier options
Driver Attribution (Explainability Output)	Identification of contributing factors (e.g., surgery, oncology, trauma)	Context-dependent	Clinical validation and manual override	Misinterpretation of model output	Engage transfusion specialists for case-level review
Inventory Stress Indicator	Alignment of forecast with current stock and depletion	Dynamic and time-sensitive	Immediate operational intervention	Stockout or wastage due to misalignment	Redistribute stock or expedite orders
Temporal Forecast Horizon (24–72h)	Short-term planning window	Increasing uncertainty with horizon length	Multi-day procurement and logistics planning	Delayed response to evolving demand	Stage orders and monitor updates iteratively

Closed-loop learning and feedback

Closed-loop learning would compare actual daily issue, reservation, wastage, and emergency order patterns with the model's prior forecast. This feedback could guide periodic recalibration as surgical practice, oncology protocols, trauma volume, or blood bank workflows change. Blood demand forecasting studies and transfusion analytics reviews emphasise that models should adapt to changing operational environments rather than remain fixed after initial development [21-23]. Continuous monitoring would also help identify when data latency, workflow changes, or coding practices begin to degrade forecast reliability.

Evaluation Strategy

Predictive performance metrics

The model should be evaluated using standard forecast error measures such as mean absolute error, root mean square error, and mean absolute percentage error by product type, without relying on any single metric alone. Prediction interval coverage should also be assessed because uncertainty is operationally meaningful for trauma, surgery, and platelet demand. Prior blood demand forecasting and platelet ordering research provides a basis for evaluating both point forecasts and decision-oriented outputs [1, 10, 21]. Evaluation should focus on whether the model would support safer and more efficient inventory decisions than routine par-level review.

Temporal validation and prospective testing

Temporal validation should use rolling or forward-looking splits so that future demand is never used to inform past forecasts. A silent prospective run would allow the model's recommendations to be compared with existing blood bank practice before any operational changes are made. Machine learning studies in transfusion and perioperative prediction show the importance of validation designs that reflect real clinical deployment rather than retrospective convenience alone [3, 7, 14]. This strategy would help determine whether the model remains credible under changing schedules, admissions, and inventory conditions.

Operational impact

Operational impact should be assessed through stockout events, expiry-related wastage, emergency courier orders, reservation pressure, and staff time spent on daily ordering review. These outcomes reflect whether the forecast improves blood bank work rather than only whether predicted demand approximates observed use. Inventory optimisation studies suggest that forecast value depends on downstream ordering, replenishment, and supply-demand matching processes [1, 2, 23]. Evaluation should therefore combine predictive accuracy with practical measures of transfusion service resilience.

Limitations

Data availability and latency

The proposed model depends on timely access to surgical schedules, trauma indicators, oncology plans, transfusion history, and inventory records. Surgical schedules may change after extraction, trauma admissions are difficult to anticipate beyond short horizons, and oncology plans may not perfectly predict actual cytopenia or transfusion timing. Prior work in perioperative, trauma, and chemotherapy-related prediction suggests that these signals are useful but inherently incomplete [3-9, 14-20, 24-29]. Data latency must therefore be treated as a core modelling limitation rather than a minor technical issue.

Generalizability across hospitals

A model developed for a high-volume tertiary hospital may not transfer directly to smaller hospitals, regional centres, or institutions with different trauma, surgery, oncology, and supplier profiles. Local transfusion thresholds, surgical case mix, platelet practices, and inventory policies can alter both demand patterns and decision consequences. Prior studies across blood demand forecasting, transfusion prediction, and donor analytics show that machine learning systems are shaped by the populations and workflows from which their data are drawn [1, 2, 21-23, 30, 31]. Multi-centre validation would therefore be necessary before broad deployment.

Conclusion

A machine learning model for daily blood product demand forecasting could help tertiary hospitals integrate clinical schedules, transfusion history, oncology treatment activity, trauma patterns, and inventory depletion into a single decision-support framework. Such a model would produce product-specific forecasts aligned with blood bank ordering cycles.

Its key strength would be the integration of scheduled and unscheduled demand drivers into an interpretable operational forecast. Product-specific outputs and uncertainty estimates could help staff distinguish routine replenishment from days requiring heightened preparedness.

Important challenges would remain in real-time data integration, modelling trauma surges, handling schedule changes, and maintaining trust among transfusion service staff. Cross-site transferability would also require careful attention because hospital case mix and blood bank workflows differ substantially.

Future work should prioritise multi-centre validation and pilot implementation within blood bank information systems. The goal should be a safe, auditable, and clinically supervised forecasting tool that improves preparedness while reducing avoidable wastage.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 19 Nov 2023 Revised: 25 Dec 2023 Accepted: 02 Feb 2024
Published online: 25 February 2024

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at https://creativecommons.org/licenses/by-nc-sa/4.0/.

References

Li N, Arnold DM, Down DG, Barty R, Blake J, Jones GL, et al. From demand forecasting to inventory ordering decisions for red blood cells through integrating machine learning, statistical modeling, and inventory optimization. Transfusion. 2022;62(1):87-99. https://doi.org/10.1111/trf.16749.

Li N, Chiang F, Down DG, Heddle NM. A decision integration strategy for short-term demand forecasting and ordering for red blood cell components. Oper Res Health Care. 2021;29:100290. https://doi.org/10.1016/j.orhc.2021.100290.

Mitterecker A, Hofmann A, Trentino KM, Lloyd A, Leahy MF, Mountford WK, et al. Machine learning-based prediction of transfusion. Transfusion. 2020;60(9):1977-86. https://doi.org/10.1111/trf.15960.

Zapf MA, Fabbri DV, Andrews J, Li G, Freundlich RE, Ehrenfeld JM, et al. Development of a machine learning model to predict intraoperative transfusion and guide type and screen ordering. J Clin Anesth. 2023;91:111272.

https://doi.org/10.1016/j.jclinane.2023.111272.

Wang Z, Zhe S, Zimmerman J, Morrisey C, Tonna JE, Brown SM, 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. https://doi.org/10.1038/s41598-022-05332-y.

Tschoellitsch T, Böck C, Maletić TT, Hofmann A, Meier J. Machine learning-based prediction of massive perioperative allogeneic blood transfusion in cardiac surgery. Eur J Anaesthesiol. 2022;39(9):766-73. https://doi.org/10.1097/EJA.0000000000001694.

Lee SM, Lee G, Kim TK, Le T, Hao J, Kim N, et al. Development and validation of a prediction model for need for massive transfusion during surgery using intraoperative hemodynamic monitoring data. JAMA Netw Open. 2022;5(12):e2246637. https://doi.org/10.1001/jamanetworkopen.2022.46637.

Feng Y, Xu Z, Sun X, Wang D, Yu Y. Machine learning for predicting preoperative red blood cell demand. Transfus Med. 2021;31(4):262-70. https://doi.org/10.1111/tme.12771.

Walczak S, Velanovich V. Prediction of perioperative transfusions using an artificial neural network. PLoS One. 2020;15(2):e0229450. https://doi.org/10.1371/journal.pone.0229450.

Mirjalili M, Abouee-Mehrizi H, Barty R, Heddle NM, Sarhangian V. A data-driven approach to determine daily platelet order quantities at hospitals. Transfusion. 2022;62(10):2048-56. https://doi.org/10.1111/trf.17067.

Engelke M, Brieske CM, Parmar V, Flaschel N, Kureishi A, Baldini G, et al. Predicting individual patient platelet demand in a large tertiary care hospital using machine learning. Transfus Med Hemother. 2023;50(4):277-85. https://doi.org/10.1159/000530418.

Engelke M, Schmidt CS, Baldini G, Parmar V, Hosch R, Flaschel N, et al. Optimizing platelet transfusion through a personalized deep learning risk assessment system for demand management. Blood. 2023;142(26):2315-26. https://doi.org/10.1182/blood.2023021798.

Li N, Down DG. Deep learning for platelet transfusion. Blood. 2023;142(26):2231-2. https://doi.org/10.1182/blood.2023023654.

Levi R, Carli F, Arévalo AR, Altinel Y, Stein DJ, Roberts RJ, et al. Artificial intelligence-based prediction of transfusion in the intensive care unit in patients with gastrointestinal bleeding. BMJ Health Care Inform. 2021;28(1):e100245. https://doi.org/10.1136/bmjhci-2020-100245.

Liu LP, Zhao QY, Wu J, Luo YW, Dong H, Ma Y, 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. https://doi.org/10.3389/fmed.2021.632210.

Chen S, Liu LP, Wang YJ, Zhou XH, Dong H, Zhao QY, et al. Advancing prediction of risk of intraoperative massive blood transfusion in liver transplantation with machine learning models: a multicenter retrospective study. Front Neuroinform. 2022;16:893452. https://doi.org/10.3389/fninf.2022.893452.

Chen Y, Cai X, Cao Z, Lin J, Huang W, Chen W, et al. Prediction of red blood cell transfusion after orthopedic surgery using an interpretable machine learning framework. Front Surg. 2023;10:1047558. https://doi.org/10.3389/fsurg.2023.1047558.

Jo C, Ko S, Shin WC, Han HS, Lee MC, Lee S, et al. Transfusion after total knee arthroplasty can be predicted using the machine learning algorithm. Knee Surg Sports Traumatol Arthrosc. 2020;28(6):1757-64.
https://doi.org/10.1007/s00167-019-05648-7.

Zhang J, Jiang L, Zhu X. A machine learning-modified novel nomogram to predict perioperative blood transfusion of total gastrectomy for gastric cancer. Front Oncol. 2022;12:826760.
https://doi.org/10.3389/fonc.2022.826760.

Liu S, Zhou R, Xia XQ, Ren H, Wang LY, Liu H, et al. Machine learning models to predict red blood cell transfusion in patients undergoing mitral valve surgery. Ann Transl Med. 2021;9(7):530.
https://doi.org/10.21037/atm-20-8015.

Twumasi C, Twumasi J. Machine learning algorithms for forecasting and backcasting blood demand data with missing values and outliers: a study of Tema General Hospital of Ghana. Int J Forecast. 2022;38(3):1258-77.
https://doi.org/10.1016/j.ijforecast.2021.11.004.

Ben Elmir W, Hemmak A, Senouci B. Smart platform for data blood bank management: forecasting demand in blood supply chain using machine learning. Information. 2023;14(1):31.
https://doi.org/10.3390/info14010031.

Li N, Pham T, Cheng C, McElfresh DC, Metcalf RA, Down DG, et al. Blood demand forecasting and supply management: an analytical assessment of key studies utilizing novel computational techniques. Transfus Med Rev. 2023;37(4):150768.
https://doi.org/10.1016/j.tmrv.2023.150768.

Benjamin AJ, Young AJ, Holcomb JB, Fox EE, Wade CE, Podbielski JM, et al. Early prediction of massive transfusion for patients with traumatic hemorrhage: development of a multivariable machine learning model. Ann Surg Open. 2023;4(3):e314.
https://doi.org/10.1097/AS9.0000000000000314.

Strickland M, Nguyen A, Wu S, Suen SC, Mu Y, Griggs C, et al. Assessment of machine learning methods to predict massive blood transfusion in trauma. World J Surg. 2023;47(10):2340-6.
https://doi.org/10.1007/s00268-023-07079-0.

Meneses E, Boneva D, McKenney M, Elkbuli A. Massive transfusion protocol in adult trauma population. Am J Emerg Med. 2020;38(12):2661-6.
https://doi.org/10.1016/j.ajem.2020.08.001.

Razzaghdoust A, Mofid B, Zangeneh M. Predicting chemotherapy-induced thrombocytopenia in cancer patients with solid tumors or lymphoma. J Oncol Pharm Pract. 2020;26(3):587-94.
https://doi.org/10.1177/1078155219853980.

Zhou S, Song B, Li C, Tang W, Zhang X, Wang Y, et al. The predictive model for risk of chemotherapy-induced thrombocytopenia based on antineoplastic drugs for solid tumors in eastern China. Sci Rep. 2023;13(1):3185.
https://doi.org/10.1038/s41598-023-30333-2.

Zhang LL, Chen X, Huang YY, Liang CX, Qiang MY, Chen J, et al. Incidence, consequences, and predictors of serious chemotherapy-induced thrombocytopenia in nasopharyngeal carcinoma. Cancer Med. 2023;12(13):14084-93.
https://doi.org/10.1002/cam4.6074.

D'Alessandro A. Red blood cell omics and machine learning in transfusion medicine: singularity is near. Transfus Med Hemother. 2023;50(3):174-83.
https://doi.org/10.1159/000531864.

Kauten C, Gupta A, Qin X, Richey G. Predicting blood donors using machine learning techniques. Inf Syst Front. 2022;24(5):1547-62.
https://doi.org/10.1007/s10796-021-10137-1.