Commentary: Optimizing Transfusion and Hemostasis Practices in Cardiac Surgery: Human versus Machine or Human and Machine?

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Commentary: Optimizing Transfusion and Hemostasis Practices in Cardiac Surgery:

Human versus Machine or Human and Machine?

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Central Message:

Machine learning models may optimize transfusion strategies and biological hemostasis for cardiac surgery, but further research is needed to inform practice changes.

Figure Legend:

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Cardiac surgery is associated with a considerable risk of bleeding and need for transfusion in up to 20-25% of cases. To best manage major bleeding, transfusion practices need to be optimized, relying on the anesthesiologist’s judgment and available objective measures, such as laboratory values, thromboelastography, or, increasingly, machine learning (ML) algorithms. Perduca et al. apply a ML model to predict biological hemostasis after cardiac surgery. Their model accurately predicted prothrombin ratio and, to a lesser extent, fibrinogen assay and platelet counts. The findings illustrate that ML models may serve as a potential decision aid tool for clinicians; however, improved model performance and multicentric, larger-sample data are needed to strengthen the role of ML models in practice.

The authors have targeted an excellent application of advanced predictive analytics as the temporal relationship between termination of cardiopulmonary bypass, return of objective markers of coagulation, and transfusion of appropriate products is important. The prediction of platelet count, prothrombin ratio, and fibrinogen assay based on patient and surgical characteristics is appropriate as using, for example, the requirement of transfusion may bias the model outcome. This type of model architecture also gives teams the autonomy and the interpretability to make transfusion decisions on an individual basis. The use of an ensemble model is highly effective as each ML algorithm parses data in a specific way and thus captures certain trends; but, in so doing, the algorithm loses other trends. An ensemble model allows for capturing all the complex ways in which predictors could be related to one another, although it increases the complexity of the model, thus requiring more data, more computational power, and reduced interpretability.

There are some limitations to ML that must be addressed. ML models with increasing complexity are often uninterpretable. As such, there should be gains in discrimination, calibration, or both, to justify the loss in model opacity. In this study, there was at most marginal improved performance of ML algorithms over linear modeling. Additionally, though
the authors collected prospective data, the use of single-center data subjects the algorithm to a batch effect. A future option is to finetune a base model, trained on general data, to the specific characteristics of a center. Federated learning or collaborative learning techniques allow for collaboration between centers for data and algorithm sharing while accounting for data privacy and protection.²

The role of ML in cardiac surgery is promising as it may improve risk prediction, reduce burdens on care teams, with endless possibilities, requiring Heart Teams to become familiar with ML and know where it can and cannot (yet?) be used.³ Simultaneously, however, it is prudent to acknowledge the limitations of ML. The frequent “black box” nature, iterative (learning) systems, and center-to-center variations of algorithms make observational comparisons and trial interventions more difficult. In addition, there are regulation and reimbursement challenges due to the continued development of new and marginally improved ML models.⁴ Lastly, the generalizability and uptake of ML across different centers vary, potentially creating a further knowhow and practice gap between well-resourced and lesser-resourced centers.⁵

Machine learning is here to stay. Acknowledging what applications are best suited for these models will ensure that the field moves toward a future wherein “human and machine” replaces the “human versus machine” discourse.
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