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Machine learning to predict haemorrhage after injury: So many models, so little dynamism

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ABSTRACT

Accurately predicting the need for blood transfusion in bleeding patients remains a critical challenge in emergency care. Machine learning (ML) models show promise for improving decision support in these scenarios, but a gap remains between research and practical application. Existing models frequently overlook the dynamic nature of clinical data, hindering their ability to provide accurate predictions for blood transfusion needs in emergency settings. We conducted a scoping review to examine ML models that integrate time-varying variables to predict blood transfusion needs in trauma patients. We discuss challenges in data collection, particularly the limitations of electronic health records (EHRs) in capturing high-quality time-series data and emphasise the need for explainable artificial intelligence (AI). We suggest future directions for research that include advancing computational approaches, improving data collection, and enhancing the interpretability of ML models to ensure their clinical relevance and utility.

Letter to the editor

The management of bleeding patients in emergency settings is a critical challenge that requires timely and informed decision-making [1]. Identifying high risk patients in need of blood transfusion can be difficult for clinicians and would benefit from decision support [2]. While machine learning models hold promise for predicting bleeding risk [3,4], a significant chasm exists between research and real-world application [5,6]. We argue here that this gap is partly attributable to the failure of these models to incorporate key decision making factors clinicians use to diagnose haemorrhage.

The resuscitation of bleeding patients requires a nuanced approach based on the dynamic assessment of vital signs and point of care blood analysis, which can rapidly evolve during treatment [7]. Trends in these variables provide crucial insights into a patient's evolving clinical status and guide timely interventions, particularly in cases of active bleeding. A rise in heart rate and lactate levels coupled with progressive hypotension after injury is suggestive of haemorrhage, prompting emergent blood transfusion. Furthermore, the patient's response to this fluid resuscitation is fundamental to assessing their degree of ongoing haemorrhage. The dynamic interplay of laboratory values, physiological markers, and response to therapy guides clinicians in their decision-making [7].

We conducted a scoping review to identify machine learning (ML) models that incorporate changes in patient variables over time to predict the need for blood transfusion. The Joanna Briggs Institute (JBI) scoping review framework was used to guide this review [8]. Publications were eligible for inclusion if they reported a ML-derived prediction model for blood transfusion that had dynamic inputs. We defined a dynamic input as a variable that included a change over time. Our search was performed in four databases: Medline, Web of Science, Embase, and Cochrane. The search terms used were ((“trauma” or “injury” or “emergency”) and (“artificial intelligence” or “machine learning” or “predictive modelling” or “algorithm”) and (“outcome prediction” or “prognosis” or “predictive analytics”) and (“haemorrhage” or “blood loss” or “transfusion”)).

This strategy yielded seven studies for inclusion (Fig. 1). Screening was conducted independently by two authors (GS and YA) and any conflicting decisions were resolved by an independent third author (MM).

After full text review, none of the seven identified articles, which described over 30 ML approaches to haemorrhage prediction, contained models that included dynamic variables.

The absence of dynamic input variables within ML models for haemorrhage prediction stands in contrast to their successful application in other clinical areas, such as acute kidney injury prediction. A recently published model which uses a Recurrent Neural Network was developed to predict acute kidney injury after paediatric cardiac surgery. The model is a “time-aware” using data collected at multiple times [9]. This approach highlights the potential of dynamic ML models to solve complex prediction challenges by effectively capturing the evolution of patient states over time.

The first challenge to incorporate dynamic variables in to haemorrhage prediction models, lies in the complexities of capturing high-quality time-series data from electronic health records (EHR) in bleeding trauma patients. Many ML models are derived from routinely collected healthcare data rather than bespoke databases for developing ML models. Additionally, EHR data can vary significantly between hospitals due to different documentation systems and methods. For example, some hospitals may use free-text entries for documenting patient information, while others employ structured tick-box formats and detailed templates to standardize data entry. Trauma EHRs typically include vital signs, laboratory results, imaging studies, medication records, and clinical notes, but the consistency and completeness of this data can vary. Data entry practices during active bleeding events can be inconsistent, leading to gaps or irregularities in the temporal representation of critical variables such as blood pressure, heart rate, and blood

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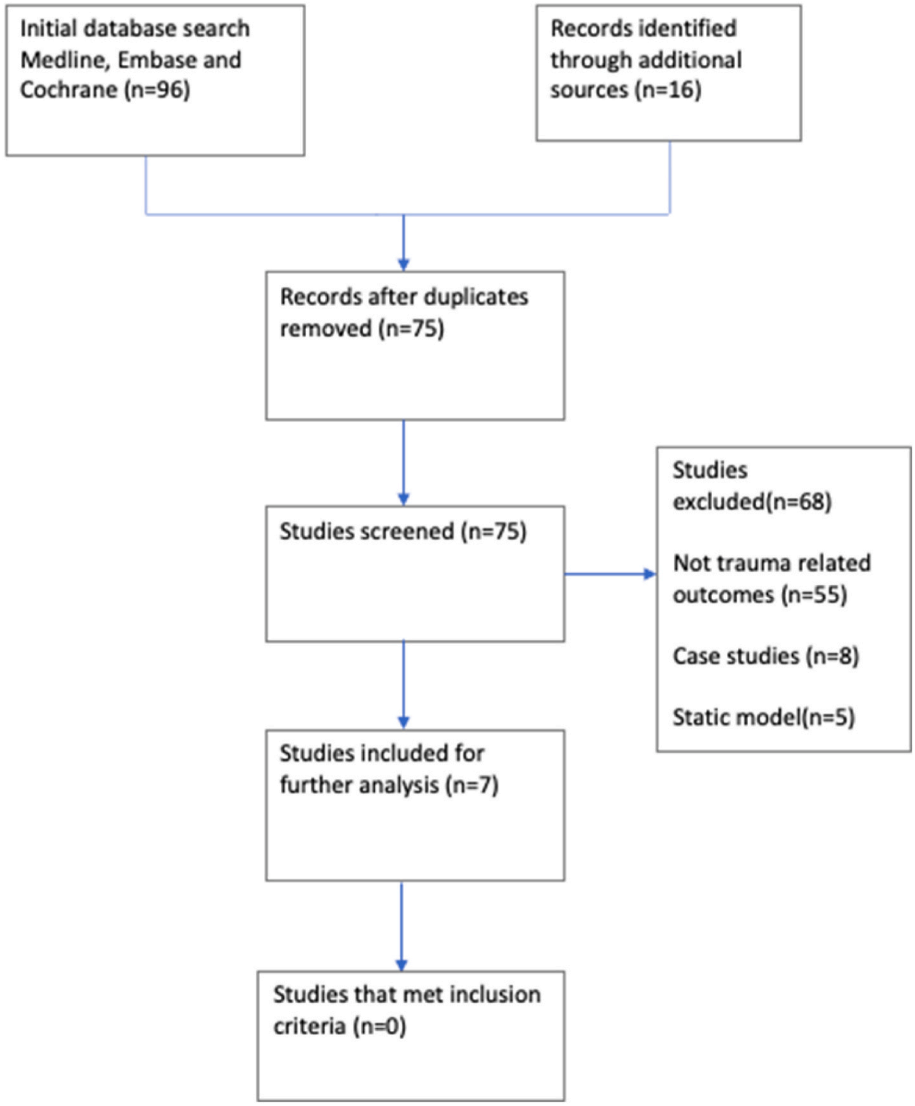

Fig. 1. PRISMA flowchart of studies included in the scoping review.

gas variables [10,11]). Issues with recording data are surmountable, however. A recent study demonstrated that a pre-hospital to emergency department increase in shock index was associated with a twofold higher risk of blood transfusion in trauma patients [12]. Even without incorporating additional patient variables, this simple model highlights the prognostic value of changes in clinical parameters over time. The study's findings suggest that incorporating dynamic changes in clinical variables, such as the shock index, into predictive models could improve the accuracy of blood transfusion risk assessment.

A second challenge that arises from dynamic AI prediction models is the ability to differentiate between pathological processes causing changes in vital signs and the effects induced by treatments. For example, an increase in blood pressure might result from the natural resolution of a pathological condition or from the administration of vasopressors. This distinction is crucial for accurate modeling and interpretation of patient data. While current literature incorporates the treatment variables as input variables, this ignores the causality aspect of observable variables (i.e. vital signs) and treatment initiated in response to these variables [13,14]. To disentangle this, using a causal framework could be helpful as demonstrated by Lim et al. in predicting tumour response to chemotherapy, radiotherapy or combination treatment [15]. The *limitation of such frameworks is the requirement high-quality data with sufficient time resolution, particularly within the changeable environment of major trauma.* Failing to differentiate between these factors can lead to misleading conclusions and impair clinical decision-making.

Third, the integration of input variables that change over time into ML models has introduced a challenging layer of complexity. To take advantage of temporal patterns of multivariate time series data, the underlying data-generating process must have regular repeated observations of the variables. Advances in computational approaches specifically designed to process sequential data and model dynamic patterns, such as Recurrent Neural Networks (RNN) or Transformers networks, are used in other domains; without the necessary volume of data required to train them, they cannot be brought to the bedside [16]· The question remains about the volume of data available and how it can be validated to add real value. Ensuring that sufficient data is available, accurate and validated is crucial for these models to be effective in clinical settings.

Finally, interpretability, and therefore usability, of these complex models may be challenging. While RNNs and LSTMs excel at capturing temporal dependencies, their inner operations can lack transparency, making it difficult for clinicians to understand and trust the model's decision-making process. If clinicians cannot understand or interpret the ML/AI model output, its usability will be negatively impacted, hampering its adoption into clinical settings [17]. It has therefore become increasingly important to ensure AI/ML is explainable to end-users [18]. Within deep learning, approaches to improve interpretability are being explored. Techniques include Shapley Additive exPlanations (SHAP) to evaluate the contributions of each feature to the model's predictions; Local Interpretable Model-agnostic Explanations (LIME) for local approximations of the model's behavior, and visualization tools to graphically represent data trends and model outputs [19]. Further work is needed to improve interpretability to clinicians in real-world settings.

Efforts should focus on ensuring the availability of high-quality time-series data for model training and validation. Standardisation of data structures and validation metrics is crucial, especially when dealing with heterogeneous data sources. Collaborations between healthcare institutions, technology companies, and academic researchers could facilitate the pooling of computational resources and expertise required to train and optimize these complex models effectively. Addressing the interpretability and usability concerns of these models should be a priority, to build trust among clinicians, and facilitate the adoption of these models in clinical practice. Overcoming these hurdles is crucial for developing clinically relevant and trustworthy ML models that can effectively incorporate dynamic variables and provide timely and accurate predictions for haemorrhage management.

CRediT authorship contribution statement

Greta Safoncik: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Yeswanth Akula:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Jared M. Wohlgemut:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Allan Pang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Max Marsden:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Ethics statement

We declare that this work complies with the relevant ethical standards. As an editorial letter, no human or animal data were collected or analysed. There are no conflicts of interest to declare, and no funding or ethical approvals were required for this work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Duchesne J, McLafferty BJ, Broome JM, Caputo S, Ritondale JP, Tatum D, Taghavi S, Jackson-Weaver O, Tran S, McGrew P, Harrell KN, Smith A, Nichols E, Dransfield T, Marino M, Piehl M. Every minute matters: improving outcomes for penetrating trauma through prehospital advanced resuscitative care. J Trauma Acute Care Surg 2024;97(5):710–5. https://doi.org/10.1097/TA.0000000000004363.

[2] Wohlgemut JM, Pisirir E, Stoner RS, Kyrimi E, Christian M, Hurst T, et al. Identification of major hemorrhage in trauma patients in the prehospital setting: diagnostic accuracy and impact on outcome. Trauma Surg Acute Care Open 2024;9(1):e001214.

[3] Oakley W, Tandle S, Perkins Z, Marsden M. Predicting blood transfusion following traumatic injury using machine learning models: a systematic review and narrative synthesis. J Trauma Acute Care Surg 2024. https://doi.org/10.1097/TA.0000000000004385.

[4] Peng HT, Siddiqui MM, Rhind SG, Zhang J, da Luz LT, Beckett A. Artificial intelligence and machine learning for hemorrhagic trauma care. Military Medical Research 2023;10(1).

[5] Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMC Med 2019;17(1):195.

[6] Tandle S, Wohlgemut JM, Marsden MER, Pisirir E, Kyrimi E, Stoner RS, et al. Enhancing the clinical relevance of haemorrhage prediction models in trauma. Military Medical Research 2023;10(1):43.

[7] Marsden MER, Kellett S, Bagga R, Wohlgemut JM, Lyon RL, Perkins ZB, et al. Understanding pre-hospital blood transfusion decision-making for injured patients: an interview study. Emerg Med J 2023;40(11):777–84.

[8] Peters MDJ, Godfrey C, McInerney P, Munn Z, Tricco AC, Khalil H. Scoping reviews. In: Aromataris E, Lockwood C, Porritt K, Pilla B, Jordan Z, editors. JBI manual for evidence synthesis. JBI; 2020. https://doi.org/10.46658/JBIMES-24-09. https://synthesismanual.jbi.global.

[9] Zeng X, Shi S, Sun Y, Feng Y, Tan L, Lin R, Li J, Duan H, Shu Q, Li H. A time-aware attention model for prediction of acute kidney injury after pediatric cardiac surgery. J Am Med Inf Assoc 2023;30(1):94–102. https://doi.org/10.1093/jamia/ocac202.

[10] Brekke IJ, Puntervoll LH, Pedersen PB, Kellett J, Brabrand M. The value of vital sign trends in predicting and monitoring clinical deterioration: a systematic review. PLoS One Jan. 2019;14(1). https://doi.org/10.1371/JOURNAL.PONE.0210875.

[11] Che Z, Purushotham S, Cho K, Sontag D, Liu Y. Recurrent neural networks for multivariate time series with missing values. Sci Rep Dec. 2018;8(1):1–12. https://doi.org/10.1038/s41598-018-24271-9.

[12] Walker PW, Luther JF, Wisniewski SR, Brown JB, Moore EE, Schreiber M, Joseph B, Wilson CT, Harbrecht BG, Ostermayer DG, Cotton B, Miller R, Patel M, Martin-Gill C, Sperry JL, Guyette FX. Prehospital Delta Shock Index predicts mortality and need for life-saving interventions in trauma patients. Prehosp Emerg Care 2024:1–7. https://doi.org/10.1080/10903127.2024.2412841.

[13] Kim SY, Kim S, Cho J, Kim YS, Sol IS, Sung Y, Cho I, Park M, Jang H, Kim YH, Kim KW, Sohn MH. A deep learning model for real-time mortality prediction in critically ill children. Scientific Reports 2019;9:12831. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC6694497/. [Accessed 14 December 2024].

[14] Su CF, Chiu SI, Jang JSR, Lai F. Improved inpatient deterioration detection in general wards by using time-series vital signs. Sci Rep 2022;12:12002. https://doi.org/10.1038/s41598-022-16195-2. [Accessed 14 December 2024].

[15] Lim B, Alaa A, van der Schaar M. Forecasting treatment responses over time using recurrent marginal structural networks. Proceedings of the 32nd conference on neural information processing systems (NeurIPS 2018). Canada: Montréal; 2018. Available at: https://dl.acm.org/doi/10.5555/3327757.3327849. [Accessed 14 December 2024].

[16] Fawaz I, Forestier H, Weber G, Idoumghar J, Muller LPA. Deep learning for time series classification: a review. Data Min Knowl Discov 2019;33(4):917–63. https://doi.org/10.1007/s10618-019-00619-1.

[17] Wohlgemut JM, Pisirir E, Stoner RS, Kyrimi E, Yet B, Marsh W, Perkins ZB, Tai NRM. Bayesian networks may allow better performance and usability than logistic regression. Crit Care 2024;28(1):234. https://doi.org/10.1186/s13054-024-05015-w.

[18] Ali S, Abuhmed T, El-Sappagh S, et al. Explainable artificial intelligence (XAI): what we know and what is left to attain trustworthy artificial intelligence. Inf Fusion 2023;99:101805.

[19] Thorsen-Meyer HC, et al. Dynamic and explainable machine learning prediction of mortality in patients in the intensive care unit: a retrospective study of high-frequency data in electronic patient records. Lancet Digit. Heal. Apr. 2020;2(4):e179–91. https://doi.org/10.1016/S2589-7500(20)30018-2.

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