Al Raizah and Alrizah *Thrombosis Journal* (2025) 23:2
https://doi.org/10.1186/s12959-025-00690-3

Thrombosis Journal

REVIEW

Open Access

Artificial intelligence in thrombosis: transformative potential and emerging challenges

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Abstract

Venous thromboembolism (VTE), including deep vein thrombosis (DVT) and pulmonary embolism (PE), continues to pose significant clinical challenges despite advancements in medical care. Artificial intelligence (AI) presents promising opportunities to enhance the diagnosis, prediction, and management of VTE. This review examines the transformative potential of AI in thrombosis care, highlighting both the potential benefits and the challenges that need to be addressed. Through an analysis of current applications and future directions, the review underscores AI's role in advancing VTE management and improving clinical outcomes.

Introduction

Venous thromboembolism (VTE), which includes both deep vein thrombosis (DVT) and pulmonary embolism (PE), represents a significant clinical challenge due to its high prevalence, morbidity, and mortality rates. Despite advances in medical knowledge and therapeutic interventions, VTE remains a leading cause of preventable hospital deaths [1]. In recent years, artificial intelligence (AI) has emerged as a transformative technology in healthcare, offering new avenues for enhancing the diagnosis, prediction, and management of various medical conditions [2]. AI encompasses various methodologies that are pivotal in healthcare applications. These include machine learning (ML), artificial neural networks (ANNs), and natural language processing (NLP), each with distinct approaches to data processing. AI's ability to process vast amounts of data and identify complex patterns presents an opportunity to overcome the limitations of conventional VTE risk assessment tools. By leveraging ML algorithms, neural networks, and other AI-driven technologies, clinicians can potentially improve the precision and efficiency of VTE management [3]. This review aims to explore the current and potential applications of AI in the field of thrombosis. Through an overview of current literature, this review will highlight the advancements, benefits, and challenges associated with integrating AI into thrombosis care. Ultimately, this review seeks to underscore the transformative potential of AI in enhancing patient outcomes and shaping the future of VTE management.

AI in thrombosis prediction

Challenges with current traditional methods for predicting the first VTE

Accurate prediction of future VTE can aid in risk benefit considerations and allow for the selection of high-risk patients who are most likely to benefit from pharmacological thromboprophylaxis. Various clinical risk

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prediction models like PADUA, CAPPRINI, IMPROVE risk scores have been developed for the prediction of VTE in different settings, but their performance varies among populations and baseline risks. Traditionally, these models are derived using regression-based analysis, such as logistic regression and Cox regression. These methods have several shortcomings, including the limitation to highly structured and curated predictor variables. As a result, these models generally have a weak ability to predict VTE accurately [4]. This represents a significant challenge with current traditional methods.

Evidence of using AI in predicting first VTE

Recent studies highlight the potential of AI and ML in enhancing the prediction of VTE. One systematic review involving 20 studies found that AI based models had a higher mean area under the curve (AUC) of 0.79 compared to 0.61 for conventional methods, indicating better predictive accuracy [5]. Another systematic review focusing on cancer patients included seven studies with 12,249 patients. The ML models demonstrated good predictive performance, with a pooled sensitivity of 0.87, specificity of 0.87, and AUC of 0.91 in the training set, and 0.65, 0.84, and 0.80, respectively, in the test set [6]. These findings suggest that AI holds promise as a valuable tool in clinical practice, potentially outperforming traditional prediction models and enhancing patient outcomes by enabling more accurate VTE predictions.

Challenges with current traditional methods for predicting recurrent VTE

Recurrent venous thromboembolism (RVTE) is a significant concern in medical practice. After an initial VTE, anticoagulation therapy is essential to prevent recurrence. However, deciding how long a patient should remain on anticoagulation therapy is complicated and must be individualized, considering many factors. Current models that predict the risk of recurrence help guide these decisions, but they have notable limitations. These models often lack sufficient predictive accuracy, have not been thoroughly validated, and fail to account for all relevant variables [7]. These issues highlight the need for better, more personalized predictive tools.

Evidence of using AI in predicting recurrent VTE

Artificial Intelligence has shown great promise in accurately predicting the recurrent VTE. AI models, particularly ANNs combined with Principal Component Analysis (PCA), enhance predictive accuracy by handling complex, multidimensional data inputs, a task where traditional methods falter. A key study explored the use of ANNs combined with PCA to reduce input variables while maintaining high predictive accuracy. The best performing model achieved an accuracy of 92.8% and an area under the curve (AUC) of 0.977 [8]. These results highlight AI's potential to significantly enhance VTE management by providing more precise predictions of recurrence risk, thereby improving patient care and clinical decision making.

AI in thrombosis diagnosis

Challenges with current traditional methods

Traditional methods for diagnosing thrombosis, such as Computed Tomographic Pulmonary Angiography (CTPA) for PE and ultrasound for DVT, are not without limitations. While CTPA is noninvasive, widely accessible, and can be rapidly performed, its effectiveness hinges on the expertise of radiologists, making the process susceptible to interpretation errors and potential delays in diagnosis [9]. Similarly, ultrasound, though a noninvasive and commonly used tool for DVT diagnosis, relies heavily on the skill of the operator, leading to variability in accuracy. These dependencies on specialized skills and the potential for variability highlight the shortcomings of traditional diagnostic methods in providing consistent and timely diagnoses of DVT and PE [10].

Evidence of using AI in thrombosis diagnosis

A large retrospective study evaluated an AI powered algorithm for detecting PE on CTPAs, analyzing 1,465 exams. The AI demonstrated high diagnostic accuracy with 92.7% sensitivity and 95.5% specificity, effectively identifying true emboli and reducing false positives [11]. Additionally, another retrospective study assessed the impact of AI on worklist reprioritization, showing that the AI tool significantly reduced report turnaround time (47.6 vs. 59.9 min) and wait time (21.4 vs. 33.4 min) for PE positive exams [12]. These findings suggest that AI can significantly aid in diagnosing PE, improving clinical efficiency, and enabling earlier interventions for acute PE.

AI in thrombosis research

Challenges with current traditional methods

Capturing VTE events for big data research is challenging. Typically, this involves using ICD codes, which have variable success rates, or manual chart reviews, which are time consuming and labor intensive [13, 14].

A systematic review and meta-analysis of 13 studies demonstrate that natural language processing (NLP) combined with ML can effectively identify VTE in free text reports. The overall performance of these methods was high, with pooled sensitivity, specificity, positive predictive value, and negative predictive value all exceeding 90%. These findings underscore AI's potential to expedite big data analysis and improve the accuracy of capturing VTE events in clinical research [15].

Table 1 Challenges and suggested solutions

Challenge	Explanation	Solutions
Data Quality and Bias	AI models often trained on biased datasets from high income countries or specific populations.	Use diverse, representative datasets for training AI models.
	Biased outputs can exacerbate healthcare disparities.	Implement bias detection and mitigation strategies in AI development.
Transparency and Explainability	AI systems often operate as "black boxes," making decisions difficult to understand.	Develop interpretable AI models to ensure transparency.
	Lack of transparency undermines trust and accountability in clinical practice.	Implement explainability tools to provide insights into AI decision making processes.
Automation Bias and Human Factors	Risk of overreliance on AI generated recommendations, even when inaccurate.	Train healthcare providers to critically assess AI recommendations.
	Overdependence on AI may lead to degradation of clinical skills.	Encourage a balanced approach, combining AI assistance with human expertise.
Ethical and Legal Concerns	Issues include patient consent, data privacy, and the potential for AI to cause harm.	Establish ethical guidelines and legal frameworks specific to AI in healthcare.
	Rapid AI advancements often outpace existing legal standards.	Regularly update legal frameworks to keep pace with AI developments.
Privacy and Security	AI systems are vulnerable due to complex data handling, increasing cyber threat risks.	Implement robust data protection measures and encryption.
	Anonymization challenges and risk of reidentification.	Use advanced anonymization techniques and regular security audits.
	Machine learning models susceptible to adversarial attacks.	Develop AI specific cybersecurity protocols to mitigate risks.
	Decentralized AI processing complicates compliance with GDPR, HIPAA, and other regulations.	Ensure strict adherence to data protection regulations and focus on organizational security.
	Insider threats and the opaque nature of AI models further complicate security efforts.	Implement strong access controls and transparency measures in AI model development.

Challenges of using AI in healthcare (table)

While AI holds significant promise in revolutionizing healthcare by improving diagnostics, treatment planning, and patient outcomes, it also presents several challenges and limitations that need to be addressed (Table 1).

Data quality and bias

One of the significant challenges in using AI in healthcare is the quality and bias of the data used to train AI models. AI systems, particularly large multimodal models (LMMs), are often trained on datasets that may contain biases, especially when sourced predominantly from high income countries or specific populations. This can lead to biased outputs that do not accurately represent diverse patient groups, potentially exacerbating healthcare disparities. Beyond selection bias, data quality issues, such as missing data or dataset appropriateness, are critical. Inadequate data can lead to inaccurate conclusions and skew AI model predictions, highlighting the necessity for high-quality, relevant datasets in AI-driven thrombosis research [16].

Transparency and explainability

AI systems, especially those involving complex algorithms like LMMs, often operate as "black boxes," making it difficult for healthcare providers to understand how decisions are made. This lack of transparency can undermine trust in AI systems and poses challenges in ensuring accountability and informed decision making in clinical practice [17].

Automation bias and human factors

Automation bias is a critical concern in the deployment of AI in healthcare. There is a risk that healthcare providers may over rely on AI generated recommendations, even when they are inaccurate or incomplete. This reliance on AI could lead to diagnostic errors or inappropriate treatment decisions, potentially causing harm to patients. Additionally, as AI becomes more integrated into healthcare, there is a concern that healthcare providers may become overly dependent on AI, leading to a degradation of clinical skills. This skill degradation could result in poorer patient outcomes, particularly in situations where AI systems fail or provide incorrect recommendations. Maintaining a balance between AI assistance and human expertise is essential to avoid these pitfalls [18, 19].

Ethical and legal concerns

The use of AI in healthcare raises significant ethical and legal challenges. Issues such as patient consent, data privacy, and the potential for AI to make decisions that could harm patients are critical concerns. The rapid advancement of AI technologies often outpaces existing legal frameworks, making it difficult to ensure that AI systems are used ethically and in compliance with legal standards [20, 21].

Privacy and security

The integration of AI in healthcare involves managing large volumes of sensitive patient data, leading to significant privacy and security challenges. AI systems are particularly vulnerable due to the complex handling of data from various sources, which increases the risk of cyber threats. Anonymization is not always sufficient, as reidentification techniques can expose personal information. AI models are also susceptible to adversarial attacks, potentially resulting in inaccurate predictions that could harm patients. While certain AI models are indeed decentralized, increasing privacy risks, there is a concurrent trend towards developing privacy-preserving, locally implemented AI solutions that adhere to data protection regulations, thus enhancing patient data security. The decentralized AI complicates compliance with privacy regulations like GDPR in Europe and HIPAA in the U.S. To address these challenges, robust data protection strategies, regular security audits, and strict adherence to regulatory standards are essential [22].

Conclusion

The future of AI in thrombosis management is promising, with potential to revolutionize diagnosis, prediction, and treatment. However, realizing this potential requires overcoming challenges such as data quality, bias, transparency, and ethical concerns. Future research should focus on developing more interpretable AI models, ensuring equitable care, and integrating AI with emerging technologies like wearable devices for real time monitoring. Collaborative efforts between AI developers, clinicians, and regulators will be key to ensuring the safe and effective implementation of AI in thrombosis care, ultimately improving patient outcomes.

Author contributions

A.A and M.A contributed equally to the conception, design, and writing of the manuscript. A.A.R. provided expertise in thrombosis and clinical application, while M.A. contributed his expertise in IT and AI. Both authors reviewed and approved the final manuscript.

Funding

No funding.

Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 25 August 2024 / Accepted: 11 January 2025
Published online: 16 January 2025

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