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Review Article

Role of Artificial Intelligence and Machine Learning in Predicting and Preventing Deep Vein Thrombosis: A Focus on Evolving Paradigms and Global Health Equity

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ABSTRACT

Deep vein thrombosis (DVT) and venous thromboembolism (VTE) constitute a considerable global health challenge, leading to a significant increase in morbidity and mortality. The burden falls disproportionately on people in Arab and African countries, who face a distinct risk environment characterized by particular genetic vulnerabilities, a high incidence of comorbidities, such as sickle cell disease, and systemic obstacles in diagnosis and data acquisition. Existing risk assessment models, primarily formulated and validated within Western populations, frequently prove inadequate in diverse contexts, thereby intensifying health disparities. This review argues that artificial intelligence (AI) and machine learning (ML) may rectify the limitations of traditional, static prediction instruments by integrating intricate, high-dimensional data for dynamic and individualized risk classification. We contend that AI is uniquely capable of addressing the healthcare equity gap through the optimization of prophylaxis strategies in resource-limited settings. The realization of this potential relies on the proactive resolution of substantial difficulties, including data bias, the "black box" phenomenon, and the urgent need for varied and representative datasets. A synchronized international effort is crucial for the creation of fair, transparent, and approved AI tools, guaranteeing that the benefits of this technological progress in DVT treatment are universally available and accessible globally.

Key words: deep vein thrombosis, DVT, artificial intelligence, machine learning, algorithmic bias, thromboprophylaxis, health equity

INTRODUCTION

Venous thromboembolism (VTE), including deep vein thrombosis (DVT) and pulmonary embolism (PE), is a primary cause of preventable inpatient deaths and significantly contributes to global cardiovascular morbidity. [1] The estimated yearly incidence is 1 to 2 per 1000 individuals in Western populations, significantly impacting the cost of healthcare and health services. Nevertheless, a solely global viewpoint conceals significant regional inequalities. Emerging data challenge Arab and African perceptions of DVT as a low-risk disease. This misperception is itself an important part of the problem, likely stemming from a vicious cycle of data shortage: a lack of robust diagnostics and registries causes under-diagnosis, creating a false impression of low prevalence. This, in turn, perpetuates the low priority of DVT care and discourages allocation of resources for data collection, further enhancing the data gap. As a result, the true burden of DVT remains concealed, often overshadowed by more visible diseases, such as infectious diseases, and other priorities. Unique genetic predispositions (e.g., a different spectrum of thrombophilia and the prominence of sickle cell disease), [2] a high burden of specific comorbidities like infectious diseases, and systemic challenges in diagnosis and data collection characterize these populations. [3,4] This intricate interaction of components provides a risk scenario that is fundamentally different from Western models, requiring a very nuanced and tailored approach to DVT care.

The issue in numerous Arab and African nations is exacerbated by prevalent underdiagnosis and a significant lack of comprehensive, population-wide data, resulting in a detrimental cycle of neglect and insufficient resource allocation. [5]

It is within this context that this review establishes its thesis: Artificial Intelligence (AI) and machine learning (ML) represent significant advancements in DVT management, serving as essential technologies that can tackle widespread issues in prediction and prevention. They present a significant opportunity to overcome existing limitations and directly tackle the healthcare gap in under-resourced regions by utilizing available data to develop more effective, equitable, and personalized DVT care pathways. Recent narrative reviews have cataloged the general applications, benefits, and limitations of AI in VTE. [6] and its specific role in prevention through ML, deep learning, and natural language processing (NLP). [7] However, neither addresses health equity or the distinct risk environment of under-resourced Arab and African populations, which is the gap this review seeks to fill.

This narrative review carefully examined pertinent literature released between January 2019 and May 2026 to identify significant developments. Electronic databases, including PubMed, Scopus, Google Scholar, and EMBASE, were queried utilizing a combination of keywords and MeSH terms: "deep vein thrombosis," "artificial intelligence," "machine learning," "prediction," "prevention," "global health," "health equity," "Arab," and "Africa." The search was enhanced by queries in Google Scholar to locate further gray literature and foundational papers. General searches were conducted to identify pertinent institutional reports and current clinical trials. The reference lists of retrieved articles were manually examined for additional relevant studies. This multi-source methodology offered a comprehensive assessment of the present landscape of AI/ML in DVT care, particularly highlighting the identification of literature pertinent to emerging paradigms and global health equality. **Table 1** contrasts the DVT risk profiles in Western, Arab, and African nations.

DEFINING AI/ML IN HEALTHCARE: A PRIMER FOR CLINICIANS

A fundamental comprehension of critical ideas is vital to recognizing the potential of these technologies. AI spans several computer science fields aimed at creating computers capable of doing activities that typically require human intellect. In comparison, ML constitutes a subset of AI that allows computers to acquire knowledge from data autonomously, without the need for explicit programming. Rather than adhering to rigid rules, ML models discern patterns and relationships in data to generate predictions. [8] Multiple ML models are particularly relevant to the therapy of DVT.

Supervised ML is used for predictive and classification tasks. The model is trained on labeled data with specified outcomes (e.g., presence or absence of DVT). Examples include Random Forest and XGBoost, which are robust models for structured data, such as electronic health records (EHRs), and often outperform conventional statistical approaches in intricate prediction problems. [9] For instance, ML models trained on routine EHR variables have predicted post-surgical DVT with high discrimination, outperforming conventional risk scores. [10]

Further, neural networks and deep learning are adaptable models capable of recognizing complex, non-linear patterns within extensive datasets, applicable to both structured data and intricate inputs such as medical images. NLP constitutes a further branch of AI that interprets unstructured free text, enabling the extraction of risk factors, diagnoses, and outcomes from clinical narratives within EHR that structured fields alone do not capture. [7]

Explainable AI (XAI) is not a distinct model category; instead, it embodies a fundamental notion. As ML models get more intricate, they may evolve into "black boxes." XAI encompasses methods and techniques that enhance the transparency and comprehensibility of a model's decision-making process for clinicians, which is essential for improving trust and ensuring safety. [11] A representative application is the use of Shapley Additive exPlanations (SHAP) to rank the routine blood-count indices most influential in a DVT prediction model, rendering the model's output interpretable to clinicians. [12]

Table 1: Contrasting DVT risk profiles: Western versus Arab/African populations.

Risk factor category	Typical Western populations	Typical Arab/African populations
Genetic predisposition	High prevalence of Factor V Leiden, Prothrombin G20210A. [3]	Lower prevalence of Factor V Leiden; higher relevance of other thrombophilias (e.g., Factor VIII, MTHFR); major risk from Sickle Cell Disease. [2,3]
Comorbidities	Cancer, obesity, and chronic heart failure.	Sickle Cell Disease, infectious diseases (e.g., HIV, Schistosomiasis), and rheumatic heart disease. [2,3]
Healthcare system	Established VTE prophylaxis protocols; robust data registries.	Significant underdiagnosis; limited access to diagnostics; scarcity of localized, population-wide data. [4]

"Arab" and "African" each encompass substantial genetic, epidemiological, and healthcare-system diversity; this table presents generalized regional patterns rather than uniform profiles.

AI AND ML IN PREDICTING DVT RISK

Limitations of Current Models

Risk assessment utilizing standardized tools, including the Caprini, Padua, and Wells scores, has been a fundamental tool for DVT prevention. Although these models offer a useful framework, they contain intrinsic limitations. They are inherently static, providing a temporal snapshot that does not reflect the dynamic progression of a patient's risk. Furthermore, they rely on a limited set of predetermined variables and assume linear connections, thus limiting their capacity to tackle complexity and nonlinear interactions. The ratings were mostly created and verified in homogeneous Western cohorts, leading to miscalibration and decreased accuracy when used in genetically and physiologically diverse Arab and African populations. [13] **Table 2** illustrates a comparison between traditional risk assessment models versus AI/ML approaches.

Methods by Which AI and ML Address These Limitations

AI and ML models are particularly effective in addressing these limitations. [9] The integration of high-dimensional data using ML models facilitates the study of large and varied datasets obtained from EHRs. This encompasses ongoing laboratory values, vital signs, prescription records, and genetic data, enabling a thorough risk evaluation.

Dynamic risk stratification using AI systems enables real-time modifications of risk scores in reaction to changes in a patient's state, such as post-surgery or during chemotherapy, promoting continuous monitoring rather than a one-time evaluation.

Beyond risk prediction, ML applications extend into prognosis and diagnosis, surpassing the capabilities of traditional scores. Prognostic models are utilized to predict the future development of DVT, making them suitable for outpatient or pre-admission screening purposes. Diagnostic models, including convolutional neural networks trained on ultrasound videos to assess vein compressibility [14] assist in the identification of individuals currently experiencing DVT. Deep learning models can enhance the interpretation of compression ultrasound or computed tomography (CT) pulmonary angiography scans, potentially improving diagnostic accuracy and efficiency in environments with a lack of expert radiologists. [14] A recent narrative review similarly reports that AI is efficient in the early detection of VTE, particularly through point-of-care AI-guided sonography and CT image processing. [6]

An increasing volume of literature substantiates the superiority of ML, with research indicating that ML models significantly exceed traditional scoring methods in predicting hospital-associated VTE and cancer-associated thrombosis. [9,10]

An increasing volume of literature substantiates the superiority of ML: in cancer-associated thrombosis, ML models have outperformed conventional risk assessment models such as the Khorana score, [9] and in postoperative orthopedic patients, Random Forest and support vector machine models predicting DVT after tibial fracture surgery achieved Area under the curve (AUCs) as high as 0.99, substantially exceeding the discrimination typically reported for traditional risk scores such as Caprini and Wells (AUC generally 0.55–0.70). [10]

AI/ML WORKFLOW: FROM DATA TO CLINICAL DECISION

Comprehending the process from raw data to clinical recommendations is essential for clarifying AI. This workflow comprises several essential, iterative stages:

1. *Data acquisition and curation*: Data is collected from sources such as EHRs, laboratory systems, and potentially wearable devices. NLP can further enrich this stage by converting unstructured clinical notes into structured, analyzable variables. [7] This step is crucial, since it involves data cleansing, which includes handling missing values, correcting mistakes, and standardizing formats. This step is often the most time-consuming portion of the process.
2. *Feature engineering*: Raw data is transformed into meaningful features or variables that the model may use for learning. A single blood pressure reading may be less informative than a metric indicating "sustained hypertension over the past 6 months."
3. *Model training and validation*: The curated dataset is partitioned, with one portion designated for model training and a separate, reserved portion used for performance evaluation. Cross-validation procedures are used to ascertain that the model generalizes properly instead of just memorizing the training data.
4. *Clinical integration*: The verified model is integrated into the clinical process. This may present as an alarm in the electronic health record, a risk score on a clinical dashboard, or a decision-support tool suggesting prophylactic prescriptions.
5. *Feedback loop*: A robust AI system is dynamic and continuously evolving. The model's performance is continuously assessed as new patient data and outcomes are produced. This feedback facilitates the retraining and enhancement of the model over time, aiding in the identification and correction of "model drift," which occurs when performance declines as clinical practices change.

Table 2: Comparison of traditional risk assessment models vs. AI/ML approaches.

Feature	Traditional models (e.g., Caprini, Wells)	AI/ML models (e.g., XGBoost, Neural Networks)
Data input	Limited, predefined variables. [9]	High-dimensional, complex data (EHR, labs, genomics). [6,7]
Risk dynamics	Static (snapshot in time). [9]	Dynamic (real-time, continuous update). [6]
Validation population	Primarily Western cohorts. [9]	Requires diverse, target population validation.
Interpretability	High (transparent scoring).	Often, a "Black Box" requires Explainable AI (XAI). [8]
Personalization	Low (one-size-fits-all). [9]	High (individualized risk profiling). [6,7]

A Framework for Developing and Sustaining Equitable AI in DVT Care is described in **Figure 1**. This framework illustrates the end-to-end operational workflow for creating, implementing, and maintaining an AI/ML model for DVT prediction and prevention. The process is iterative and emphasizes equity at each stage. It begins with Data Acquisition and Curation (1), where diverse data from EHRs, laboratories, and potential wearable devices are gathered, cleaned, and standardized to mitigate bias. This feeds into Feature Engineering and Model Development (2), where meaningful predictive variables are created, and models are trained on partitioned datasets. The model then undergoes rigorous Validation and XAI Integration (3) on held-out data and diverse populations to ensure generalizability and transparency, producing an interpretable risk score. Once validated, the model is embedded into the Clinical Integration and Decision Support (4) phase, where it provides alerts and prophylaxis recommendations within clinical dashboards or EHRs. Finally, a continuous Feedback Loop and Monitoring (5) uses new patient data and outcomes to monitor for model drift and performance degradation, triggering model retraining to ensure sustained accuracy and equity over time. The central pillar of "Diverse and Representative Data" underscores that this entire cycle depends on foundational data equity.

AI AND ML IN PREVENTING DVT: OPTIMIZING PROPHYLAXIS

The Prophylaxis Dilemma

The successful prevention of DVT depends on the appropriate use of thromboprophylaxis. This choice entails intricate considerations, balancing the danger of thrombosis with the risk of hemorrhage. The difficulty is intensified in resource-constrained environments, where the rationale for drug expenses must be meticulously validated.

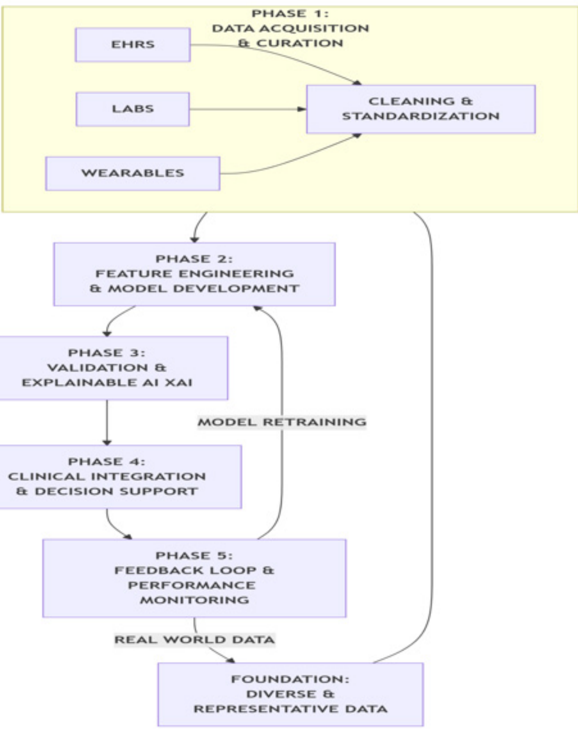

Figure 1: The operational framework for developing equitable AI in DVT care.

AI and ML Role in Prevention

The role of AI is to enhance precision and efficiency in this essential process.

- *Tailored Prophylaxis Recommendations*: AI systems may evaluate an individual's extensive clinical profile to indicate the requirement of prophylaxis, as well as the most appropriate kind and dose, thereby improving adherence to recommendations and minimizing risks. [15]
- *Predicting Prophylaxis Failure*: ML models can identify patients receiving standard prophylaxis who are at elevated risk for "breakthrough" DVT, facilitating pre-emptive intervention. [9]
- *Equity Issues*: Resource optimization in hospitals throughout Africa and the Arab world necessitates the precise targeting of costly interventions to those patients who will derive the greatest benefit, highlighting an issue of equity. AI can optimize the allocation of limited resources to achieve maximum impact.
- Models built on inexpensive, universally available inputs are especially suited to such settings; for example, a machine-learning model trained solely on routine blood-count indices discriminated DVT cases from controls with area-under-the-curve values exceeding 0.8 across six algorithms, demonstrating that accurate risk estimation need not depend on costly infrastructure. [12]

LIMITATIONS, ETHICAL CHALLENGES, AND THE PURSUIT OF EQUITY

The transformative potential of AI in DVT care is evident. Nevertheless, its path to equitable implementation is fraught with challenges that, if unaddressed, might exacerbate the disparities. A comprehensive investigation reveals that these constraints are not only technical barriers but are profoundly linked to issues of equity and justice. This assessment is consistent with recent literature identifying data bias, limited model transparency, and the absence of mature regulatory frameworks as the principal barriers to integrating AI into VTE practice. [6] All these processes are illustrated in **Figure 2**.

Vicious Cycle of Data Bias and the Digital Divide

The primary concern is a downward spiral of inequality fueled by data and infrastructure. This cycle has two interrelated components.

- *Data bias and scarcity***:** AI models are mostly trained on extensive, curated datasets derived from Western populations. When used for Arab and African populations characterized by unique genetic, comorbid, and environmental risk factors (**Table 1**), these models exhibit algorithmic bias, resulting in miscalibration and diagnostic inaccuracies. Pivotal research by Obermeyer et al. illustrated how a prevalent commercial algorithm systematically marginalized Black patients by using healthcare prices as a surrogate for need, thereby maintaining racial prejudice. [16] Subsequent work has both corroborated this pattern of algorithmic bias in other clinical prediction tools and proposed technical and procedural corrections to mitigate it, indicating that the field has moved from documenting the problem toward actively addressing it, rather than treating Obermeyer et al. as an unanswered final word. This "performance degradation" in many contexts is not a trivial defect but a fundamental shortcoming that exacerbates existing health disparities.

- *The digital divide*: Characterized by disparities in computer resources, internet connectivity, and local AI expertise, it impedes resource-limited organizations from generating their own representative data or developing context-specific models. The consequence is a harmful cycle: inadequate local data compels reliance on erroneous foreign models, yielding worse outcomes, which in turn deteriorate investment in local digital infrastructure and perpetuate data scarcity.

Breaking this cycle requires a fundamental shift from developing AI for these populations to cooperatively building AI with them.

XAI: An Ethical and Practical Imperative

The "black box" issue of intricate ML models transcends a mere technical constraint; within a global health framework, it is a significant obstacle to trust and acceptance. In congested clinical environments, a practitioner is unlikely to implement an AI proposal without comprehending the underlying logic. XAI is hence both an ethical and a pragmatic imperative. It guarantees that doctors can rely on and validate the model's output, detect any biases, and use the technology as an educational resource. In the absence of transparent and interpretable models, even a technically precise AI would struggle to assimilate into clinical procedures, hence limiting its scalability and efficacy.

Model Drift and the Challenge of Sustained Performance

The issue of model drift (declining model performance over time) is significantly exacerbated in global health. An AI model for DVT risk is not implemented in a static setting. More significantly, a model first trained on Western data may be inherently miscalibrated for a new population from the outset, representing a sort of "instantaneous drift" resulting from demographic mismatch. Continuous monitoring and validation of local data streams are essential for identification and rectification, requiring sustained investment in data curation and technological proficiency, often absent in resource-constrained settings.

Logistical and Regulatory Hurdles

Alongside these essential equity-related issues, significant logistical and regulatory challenges remain. The regulatory framework for adaptive AI-driven software as a medical device is still being developed, leading to uncertainty.

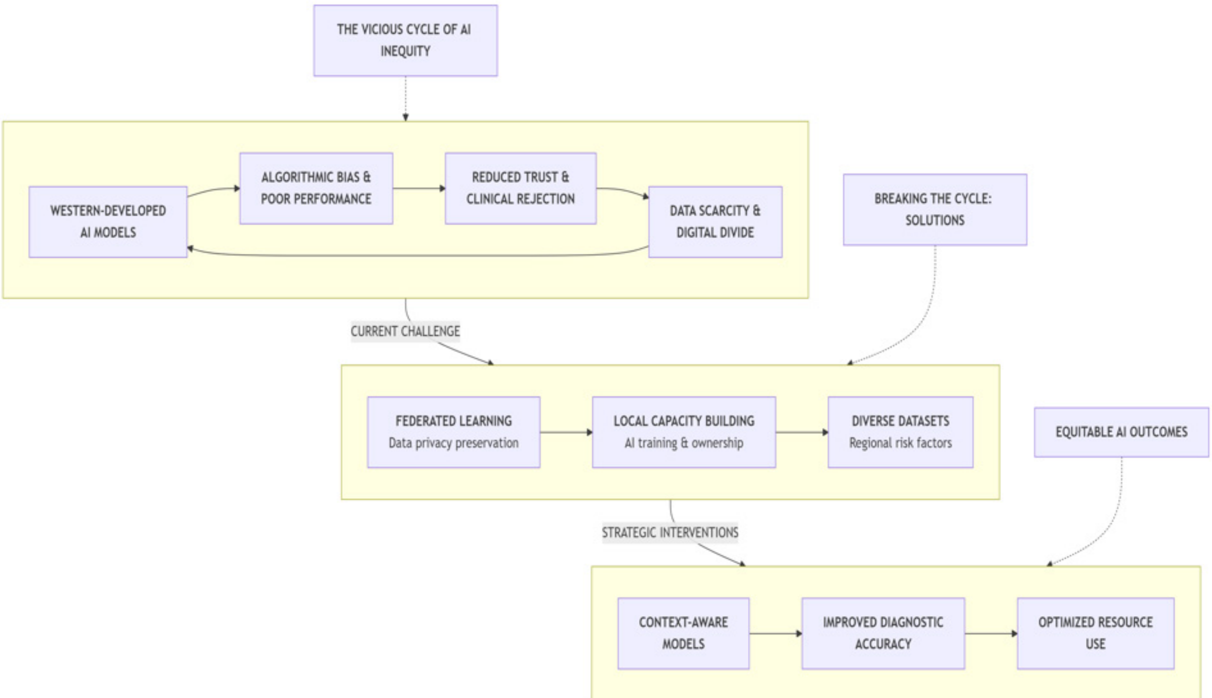

Figure 2: Transforming DVT care: breaking the cycle of AI inequity. The figure outlines the pathway from the current challenges in AI development for DVT care to equitable outcomes through strategic interventions. The Current Challenge is a vicious cycle where Data Scarcity and the Digital Divide lead to algorithmic bias and Poor Performance, which in turn causes Reduced Trust & Clinical Rejection, further perpetuating the data gap. To break this cycle, Strategic Interventions are required, including Federated Learning to preserve data privacy, Local Capacity Building to ensure AI training and local ownership, and the curation of Diverse Datasets that incorporate regional risk factors. The successful implementation of these solutions leads to Equitable AI Outcomes, characterized by Context-Aware Models, Improved Diagnostic Accuracy, and Optimized Resource Use in global DVT care.

Moreover, clear legal and professional frameworks for accountability are crucial to assign responsibility in instances when AI-generated advice causes patient harm. The substantial computational expenses associated with training and operating intricate models may be prohibitive, thereby restricting their use to affluent institutions within a region and fostering intra-regional equity disparities.

These recurring computational costs are compounded by substantial upfront capital investment in hardware, data infrastructure, and staff training, which represents a significant barrier to entry independent of any long-term savings AI may eventually deliver.

Patient-Centric Dimension: Literacy and Accessibility

The difficulties of equity transcend the clinic and the algorithm, affecting the patients directly. The digital gap, as described in The Vicious Cycle of Data Bias and the Digital Divide, encompasses not only infrastructure but also capabilities. [8,11] AI's potential in DVT care includes patient-focused tools for education and monitoring adherence; however, these tools may fall short if they do not consider the end-user. Moreover, the creation of patient-oriented AI solutions for education or adherence monitoring must consider diverse levels of health and computer literacy. Equitable AI necessitates clinically useful XAI models for clinicians and patient-centric designs that are accessible and comprehensible to the varied populations they serve. [11,13] This requires an emphasis on culturally suitable design, low-bandwidth capabilities, and collaboration with local community health networks to guarantee that these modern technologies do not unintentionally marginalize the patients who might benefit the most. The key challenges and proposed mitigations for equitable AI in DVT care are summarized in **Table 3**.

ROADMAP FOR IMPLEMENTATION: A CALL TO ACTION

A comprehensive, logical, multi-faceted, and incremental strategy is essential to resolve the concerns outlined in Section 6 and to realize the equitable potential of AI in DVT therapy.

Phase 1: Foundation and Co-Development (Next 1–2 Years)

- *Establish international consortia:* Forge partnerships focused on VTE among Arab and African populations, coordinated through bodies such as the World Health Organization (WHO), the International Society on Thrombosis and Hemostasis (ISTH), and regional thrombosis and hemostasis networks in Africa and the Arab world. Prioritize federated learning frameworks to consolidate data insights while maintaining privacy and data sovereignty.
- *Curate diverse datasets***:** Secure funding from global health organizations and national governments to create high-quality, representative, and ethically sourced databases.
- *Develop standards***:** Implement established reporting criteria for AI in VTE (e.g., TRIPOD-AI) to ensure rigorous and transparent development.

Phase 2: Validation and explainability (Years 3–5)

- *Conduct rigorous randomized controlled trials (RCTs):* Conduct prospective, randomized controlled studies in varied, real-world settings to validate that AI-driven DVT therapy improves patient prognosis (e.g., decreases DVT incidence and prevents bleeding complications of DVT therapies and prophylaxis) and is cost-effective.
- *Advance and integrate XAI***:** Design, verify, and progressively enhance user-centric XAI interfaces in partnership with local doctors. The objective is to develop technologies that provide straightforward explanations seamlessly incorporated into healthcare processes to enhance confidence and acceptance. [11]

Phase 3: Implementation, Scaling, and Sustainability (> Year 5)

- Develop deployment toolkits: Develop open-access application manuals addressing technological incorporation, clinical training, and change management for resource-constrained environments, including distribution via open-source model repositories (e.g., Hugging Face and Zenodo).
- Focus on capacity building and local ownership: Educate local IT and healthcare professionals to manage, boost, and take responsibility for the AI systems, ensuring enduring sustainability and alignment with local requirements.
- Establish continuous monitoring systems: Establish mechanisms for post-deployment monitoring to evaluate model drift, medical efficiency, and unintended effects to provide a feedback loop for continuing improvement.

DISCUSSION

This review establishes the potential of AI/ML to revolutionize DVT care, asserting that its most significant impact is

Table 3: Summary of key challenges and proposed mitigations for equitable AI in DVT care.

Challenge	Proposed Mitigation / Path Forward
Data scarcity and bias [13]	Build consortia for federated learning; fund diverse data curation.
"Black Box" problem and lack of trust [8]	Develop and integrate Explainable AI (XAI) tools; conduct user-centered design with clinicians. [8]
Lack of validation	Conduct prospective RCTs in diverse, real-world settings.
Regulatory and logistical hurdles	Create adaptive approval pathways; develop implementation toolkits for low-resource settings.

in addressing global health equity gaps. The analysis demonstrates that AI's capacity for dynamic, personalized risk stratification effectively mitigates the fundamental limitations of traditional models. [10,13] The capacity of these systems to enhance prophylaxis in resource-constrained environments is notably significant. [9,17]

The primary conclusion is that the standard trajectory of AI development will intensify existing disparities. The ethical imperative of creating equitable AI is as crucial as the associated technological difficulty. The issues of data bias, model opacity, and the digital divide represent significant challenges to the responsible implementation of this technology. [11,16]

The proposed roadmap outlines a clear direction for future progress. The necessity for diverse data, federated learning, and targeted trials is both an ethical and operational requirement. The aim is to develop universally resilient and equitable care models that are verified and successful for all groups, instead of establishing separate, parallel systems. This strategy seeks to guarantee that developments in precision medicine are inclusive of the global majority.

CONCLUSIONS

AI and ML are set to transform the management of DVT, transitioning from a reactive, uniform methodology to a proactive, accurate, and individualized strategy. The ultimate standard for this technological accomplishment will be its impact on global health equality. The considerable promise of AI to mitigate healthcare inequities for marginalized populations in the Arab world and Africa will remain unfulfilled unless the prevailing concerns of data bias and inadequate validation are effectively addressed. The future of equitable DVT care relies on a dedicated, worldwide initiative to develop AI technologies that are intelligent, inclusive, explainable, and accessible to everyone.

AUTHORS' CONTRIBUTION

All authors have significantly contributed to the work, whether by conducting literature searches, drafting, revising, or critically reviewing the article. They have given their final approval of the version to be published, have agreed with the journal to which the article has been submitted, and agree to be accountable for all aspects of the work.

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The authors disclose the use of AI technologies in the preparation of this manuscript, specifically for linguistic refinement, content restructuring, and figure creation. Despite this assistance, the intellectual framework, analysis, and scholarly conclusions remain the exclusive original work of the authors.

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