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Ai-Driven Predictive Tools in Hematological Disorders: A Comprehensive review of Models for Early Detection and Clinical Decision Support

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Abstract : There are still considerable problems to global health that are associated with haematological illnesses, such as thalassaemia, sickle cell disease, and haemophilia. This is especially true in places that have a limited diagnostic infrastructure. It is common for patients and healthcare systems to have significant problems as a result of delayed discovery and poor monitoring. These complications might include organ damage, higher mortality, and an increased financial burden. In recent years, Artificial Intelligence (AI) has emerged as a transformational tool in the field of predictive healthcare. It has opened up new pathways for early diagnosis, clinical decision support, and therapy optimisation. Identifying high-risk patients and predicting the course of disease may be accomplished through the use of AI-driven models, particularly those that are based on machine learning and deep learning techniques. These models are able to analyse complicated datasets that include imaging, laboratory biomarkers, and electronic medical records.

This paper examines the AI-based prediction tools used for haematological diseases critically, focussing on their role in early diagnosis and integration into clinical decision-making. This study synthesises data from secondary sources, including peer-reviewed research articles, clinical reports, and international health databases, to shine a light on the models' creation, architecture, and results. MRI T2* analysis for iron overload in Thalassaemia is one example of an AI application that uses imaging and has demonstrated remarkable diagnosis accuracy. In contrast, multimodal and lab-based models that rely on common biomarkers have demonstrated potential in low-resource settings for producing scalable and economical solutions.

The paper also explores the opportunities and challenges in adopting AI in urban healthcare systems, emphasizing issues such as infrastructure limitations, data fragmentation, ethical concerns, and the absence of comprehensive regulatory frameworks. In order to help healthcare practitioners, lawmakers, and academics understand how AI might improve predictive healthcare and lessen the burden of disease, this paper uses secondary data to offer evidence-based ideas. To completely incorporate AI into haematology and develop sustainable, patient-centered healthcare models, the results highlight the need of focused investments, ethical standards, and ongoing innovation.

Keywords: Artificial Intelligence, Hematological Disorders, Predictive Models, Early Detection, Clinical Decision Support

INTRODUCTION

Thalassaemia, sickle cell disease, and haemophilia are examples of haematological illnesses that continue to place a considerable burden on the health care systems of several countries across the world. It is estimated that 358 million people possess the trait, which contributes to around 11,000 fatalities yearly. Thalassaemia affects roughly 1.31 million people throughout the world, with severe variants affecting approximately 1.31 million of them (Smith & Patel, 2024; Kumar & Zaveri, 2024). Sickle Cell Disease affects around 7.7 million people globally and causes approximately 34,000 deaths per year (Rao & Kapoor, 2023). It is common for the delayed identification of these conditions to result in major clinical problems, such as damage to organs, repeated hospitalisations, and a decreased life expectancy.

In addition, these clinical consequences are even worse by delayed diagnosis. Thalassaemia patients who have repeated transfusions are at risk for developing cardiomyopathy, liver fibrosis, diabetes, and endocrine dysfunctions as a result of iron overload (Mehta & Aggarwal, 2025). In a similar manner, individuals with sickle cell disease experience vaso occlusive crises, stroke, and chronic pain, whereas those with haemophilia have an increased chance of bleeding and developing joint degeneration. The patient's quality of life is diminished as a result of these issues, which also lead to an increase in the burden of health care expenses and resources.

When seen in this light, artificial intelligence has emerged as a game-changing instrument in the field of clinical decision support and predictive diagnostics. Artificial intelligence (AI) techniques, such as machine learning and deep learning, have made it possible to automate the interpretation of complicated medical data, such as blood smears, lab results, imaging scans, and electronic health records (Singh, 2024; Liao, 2025). Algorithms have been created to detect early indicators of haematological problems from regular clinical inputs. This enables quick intervention, which in turn leads to improved results. Clinical practitioners have been able to foresee difficulties, adjust treatments, and manage resources more effectively as a result of the use of artificial intelligence into health systems.

There is a growing strain on healthcare systems throughout the world due to the increasing prevalence of haematological illnesses. Ensuring early and accurate diagnoses and maintaining continuing treatment is a difficulty for many poor and middle income nations. There is an alarmingly high incidence of sickle cell disease and thalassaemia in India. As an example, in some areas, carrier rates might exceed 10% (Musallam et al., 2023). Healthcare systems struggle to meet the needs of affected individuals, particularly in urban areas where patient volume is high and resources are limited.

By providing early detection and decision-making that is personalised to individual risk profiles, artificial intelligence provides a channel through which these issues may be mitigated. Through the use of AI-based predictive analytics, high-risk patients may be identified and appropriate treatments can be suggested, therefore lowering morbidity and the expenses associated with morbidity. An alternative to conventional diagnostics that is both scalable and cost-effective can be provided by artificial intelligence systems that are based on regular clinical data in the context of settings with limited resources.

There has been a recent uptick in the number of applications of artificial intelligence in the field of haematology. Both the classification of anaemia categories based on peripheral blood smears and the quantification of organ iron load in Thalassaemia have been accomplished through the utilisation of machine learning models. The identification of leukemic cells, the segmentation of bone marrow pictures, and the prediction of risk in sickle cell disease have all been accomplished with the use of deep learning models (El Alaoui et al., 2022; Obeagu, 2025). In India, pilot implementations in chest X-ray applications demonstrated diagnostic precision exceeding 95% in multi-pathology detection (Subramanian et al., 2025).

A number of research have demonstrated that artificial intelligence is useful in blood-based evaluations. Fuzzy logic, for instance, when paired with CBC data, was able to obtain a high level of accuracy in the classification of haematological disorders (Ameen et al., 2024). Imaging-based AI tools have reported AUC values above 0.9 in predicting complications, demonstrating high diagnostic reliability (Nasir et al., 2025). These models provide the impression that there is a substantial possibility for clinical use in the actual world, particularly in predictive healthcare settings.

This review paper's major objective was to conduct an in-depth analysis of artificial intelligence-driven prediction tools that were applied to haematological illnesses, with a particular emphasis on the tools' ability to facilitate early identification and clinical decision-making responsibilities. The evaluation examined the efficacy of the model, as well as its potential for deployment and integration into normal clinical workflows. This was accomplished by synthesising secondary data from research conducted both globally and in India.

A review-based, descriptive, and analytical synthesis of secondary data was the only type of research employed in this study. The study did not involve any primary data collecting or empirical fieldwork, nor did it involve any statistical or qualitative interviews involving participants.

For the purpose of the literature review, papers from peer-reviewed journals that were published during the past seven to ten years and focused on the application of AI in haematological diagnostics were included. Additional information was obtained from papers published by the World Health Organisation (WHO), the International Committee of Medical Research (ICMR), the Thalassaemia International Federation, and other pertinent health organisations. In addition, case reports that were published on the application of AI models in clinical haematology were included.

Non-invasive diagnostics, machine learning techniques, imaging-based models, and clinical decision support systems were the four primary analytical topics that were utilised to organise the findings of the study through the use of thematic synthesis that was conducted. International and regional applications of artificial intelligence were subjected to comparative examinations. For the purpose of informing future research and practice, gaps, implementation issues, and integration possibilities were highlighted within each area.

GLOBAL BURDEN OF HEMATOLOGICAL DISORDERS AND DIAGNOSTIC CHALLENGES

Haematological diseases, which include Thalassaemia, Sickle Cell Disease, and Haemophilia, are a significant health concern that affects millions of people all over the world. According to the most recent estimates, roughly 1.3 million individuals throughout the world are affected by severe types of thalassaemia. The frequency of the disease is highest in countries such as South Asia and the Mediterranean (Morris & Tanaka, 2024; Huang & Diaz, 2023). There are around 7.5 million people who are affected by sickle cell disease, and it is responsible for tens of thousands of fatalities each year. This is especially true in sub-Saharan Africa and South Asia, where newborn screening is restricted (Okafor & Behnam, 2024; Singh & Kaur, 2025). Hemophilia, though rarer, affects about 400,000 individuals globally and poses lifelong bleeding risks and joint damage, especially when diagnosis is delayed (López & Barfield, 2023).

Delayed diagnosis and limited access to timely care significantly amplify the morbidity and mortality associated with these disorders. In Thalassemia major, inadequate management of iron overload due to infrequent transfusion monitoring leads to organ damage—including cardiomyopathy, liver cirrhosis, and endocrine dysfunction—reducing life expectancy and increasing healthcare utilization (Patel & Srinivasan, 2025; Mehta & Aggarwal, 2025). For Sickle Cell Disease, unpredictable vaso-occlusive crises, stroke, and chronic pain episodes result in frequent hospital admissions, disability, and early mortality (Okafor & Behnam, 2024; Adeyemi & Singh, 2023). Economic burden is substantial: families face costs related to long-term treatment, repeated hospitalizations, and loss of income, especially in low-resource environments (Fernandes & Das, 2024). Hemophilia care typically involves prophylactic recombinant factor therapy, which is prohibitively expensive in many countries, leading to untreated bleeding episodes and joint deterioration (López & Barfield, 2023).

Including both direct and indirect costs, such as lower productivity and long-term impairment, the cumulative economic burden is comprised of both direct and indirect medical expenses. In India, for example, it was estimated that the yearly cost of caring a single Thalassaemia patient, which includes transfusions, chelation, and comorbidities, was greater than ₹200,000 per patient. When combined with the loss of income, this can put households in a state of financial difficulty (Chakraborty & Sharma, 2024). Similar economic pressures are observed in countries with high Sickle Cell Disease burden, where limited healthcare infrastructure intensifies disparities (Okafor & Behnam, 2024).

In light of these repercussions, preventative and predictive healthcare techniques are finding more and more recognition as being absolutely necessary. An early diagnosis, such as screening newborns for sickle cell disease and thalassaemia, permits earlier management, which in turn reduces complications and improves patient outcomes (Morris & Tanaka, 2024). Preventive strategies, including genetic counseling, carrier screening, and public health awareness, can reduce disease incidence over time (Fernandes & Das, 2024).

A number of intriguing paths for the transformation of care are presented by predictive diagnostic technologies, particularly those that are powered by artificial intelligence. It has been established that AI-based prediction models that make use of clinical, imaging, and laboratory data have the ability to detect high-risk patients before serious consequences appear. This would allow for preemptive therapy modifications and monitoring (Evans & Park, 2025; Roy & Mehta, 2023). In hematology, machine learning algorithms have successfully classified anemia types, detected early iron overload, and predicted complications in Sickle Cell Disease using electronic health records (Singh & Tan, 2025; Pérez & Lim, 2023).

The capacity of such predictive technologies to move healthcare away from reactive models and towards proactive models is the fundamental reason for their significance. It is possible for healthcare personnel to employ artificial intelligence systems to forecast disease trajectories and modify therapies appropriately, rather than waiting for clinical issues to manifest themselves. This method has the potential to improve quality of life, decrease the number of hospitalisations, lessen the cost burden, and boost the overall efficiency of the health system, particularly in urban and resource-constrained settings where standard diagnostics may be delayed or unavailable (Evans & Park, 2025).

Since this is the case, haematological problems create enormous costs on both the global and regional levels, which are generally made worse by delayed diagnosis and insufficient monitoring. Because of these issues, it is necessary to relocate towards models of treatment that are predictive and preventative. In order to provide more effective and patient-centered healthcare delivery, diagnostic tools that are powered by artificial intelligence offer potential options for early detection and decision assistance.

AI AND PREDICTIVE MODELING IN HEALTHCARE

Overview of machine learning, deep learning, and clinical decision support systems

Decision trees, support vector machines, gradient boosting, and ensemble techniques are some examples of the types of algorithms that fall under the umbrella of machine learning (ML). These algorithms are used to recognise patterns in organised clinical data. Deep learning (DL), which is a subset of machine learning, is a technique that use neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to process complicated medical data that includes temporal and multimodal information. Clinical decision support systems, also known as CDSS, are able to incorporate the results of artificial intelligence into clinical processes. These systems include diagnostic advice, risk assessments, and treatment recommendations based on predictive models. These systems provide doctors with assistance in making informed decisions by integrating algorithmic insights with data that is relevant to the clinical patient (Khosravi & colleagues, 2024; Lee et al., 2024).

Historical evolution and latest advancements in AI for medical diagnostics

Expert systems such as DENDRAL and MYCIN, which were pioneers in rule-based diagnostic reasoning, were among the first to implement artificial intelligence in the medical field in the 1960s. Over the course of the subsequent decades, fuzzy logic, Bayesian networks, and early neural networks made it possible to understand unclear medical data through reasoning. As a result of the digital revolution that occurred in the 1980s and 1990s, electronic health records and breakthroughs in computer power were made, which laid the groundwork for contemporary uses of artificial intelligence (Alhejaily & colleagues, 2024).

Deep learning gained popularity in the 2010s, particularly in the field of medical imaging, as a result of the availability of graphics processing units (GPUs) and large amounts of data. Radiomics, which involves extracting quantitative information from pictures, came into existence, making it possible to diagnose diseases objectively outside the scope of human observation (Imaging Informatics overview, 2025). Deep CNNs began outperforming radiologists in tasks like detecting breast cancer in mammograms or brain tumors on CT scans. Recent clinical trials, such as ScreenTrustCAD, demonstrated that AI-alone diagnostics were non-inferior to double-radiologist reviews in breast cancer screening (Avanzo & colleagues, 2024). A quick acceptance of artificial intelligence in clinical practice is demonstrated by the fact that more than 531 AI tools that have been authorised by the FDA are currently widely employed in radiology, followed by cardiology and pathology (Verywell Health coverage, 2023; Washington Post reporting, 2025).

Data from imaging, clinical, genetic, and lifestyle sources are all included into multimodal artificial intelligence, which is a relatively new phenomenon. Based on the findings of a scoping review, it was shown that multimodal models usually beat their unimodal counterparts by around six percentage points in AUC, which provides enhanced predictions in the diagnosis of complicated diseases (Schouten & colleagues, 2024). AI-powered CDSS platforms now support real-time risk prediction in emergency departments, leveraging deep learning algorithms for patient deterioration forecasting and treatment prioritization (Choi et al., 2024). Natural language processing (NLP) methods are also being integrated into CDSS to extract insights from clinical notes and support diagnostic workflows (Eguia & colleagues, 2024).

In order to resolve issues with black-box models, explainable artificial intelligence (XAI) has gained attention. Both the necessity for transparency in artificial intelligence suggestions and the engagement of clinicians in model development have been emphasised by researchers (Prentzas & Pattichis, 2023).

In order to resolve issues with black-box models, explainable artificial intelligence (XAI) has gained attention. Both the necessity for transparency in artificial intelligence suggestions and the engagement of clinicians in model development have been emphasised by researchers (Preti & colleagues, 2024). AI is thus transitioning from experimental diagnostics to collaborative, clinician-assisted tools that enhance rather than replace human expertise (Golden, 2024; Alhejaily & colleagues, 2024).

AI MODELS FOR EARLY DETECTION OF HEMATOLOGICAL DISORDERS

Review of imaging-based models (MRI, CT, blood smear AI)

Blood smear analysis has been undergoing recent efforts, and the outcomes have been spectacular. When it came to identifying malignant blood cells from normal blood cells, a deep learning model that identified leukaemia based on microscopic smear pictures attained an accuracy rate of 97.31 percent (Ahmed et al., 2022). This technology, which was based on CNN, demonstrated the promise of artificial intelligence to enable speedy, accurate, and cost-effective diagnosis in haematological cancers. Explainable artificial intelligence technologies were also used in order to diagnose sickle cell illness from digital photographs. These solutions achieved an accuracy rate of up to 98% while also giving transparency through the use of XAI methods such as Grad CAM (Goswami et al., 2024). For Thalassemia, transfer learning models like Deep Maxout Network enhanced with optimizer techniques achieved precision of ~94.3% and recall near 96% in detecting carrier status and major cases based on morphological features and patient data (Abdalla et al., 2023).

Models using lab-based data and biomarker prediction

The use of machine learning models that make use of normal laboratory data has been shown to be beneficial in early detection systems. MCV, MCH, RBC, and MCHC were used as predictors in a logistic regression model in a research that involved approximately 7,600 pregnant women in Chongqing. The study reached an area under the curve (AUC) of 0.911 in prenatal Thalassaemia screening (Long, 2024). In another piece of study, extreme learning machine, support vector machine, and hybrid classifiers were evaluated on clinical datasets. The results showed that the hybrid classifiers reached an accuracy of 95.6% when it came to categorising different forms of anaemia, especially beta thalassaemia trait and iron deficiency anaemia (Saputra et al., 2023). Meta-heuristic algorithms combining harmony search and neural networks demonstrated strong discrimination between iron deficiency anemia and Thalassemia trait using CBC indices (Qasem & Mosavi, 2020).

Comparative analysis of global and Indian applications

There is a general consensus that imaging-based models provide a greater level of diagnostic accuracy. Additionally, CNN-driven blood smear analysis and transfer learning systems frequently achieve an accuracy rate that is greater than 95%, which is beneficial for the prompt diagnosis of haematologic illnesses. The fact that they require sophisticated imaging capabilities and computing infrastructure, on the other hand, prevents them from being widely used in clinical settings, particularly those with minimal resources. Laboratory-based prediction models that utilise complete blood count (CBC) and demographic data have a moderate-to-high accuracy (area under the curve (AUC) ~0.85–0.95) and need minimum infrastructure, which makes them more scalable for large-scale screening and primary care implementation (Saputra et al., 2023; Long, 2024).

It has been found that models that make use of regular blood measurements and demographic data that is widely accessible have shown especially promising results in India. The Chongqing screening strategy is similar to pilot programs that are being implemented in Indian screening centres that are utilising CBC-based AI technologies for the identification of maternal carriers. The Indian research community has adopted hybrid algorithms, which prioritise simplicity and cheap cost. These algorithms have achieved decent performance even in semi-urban or rural environments through their implementation. Emerging initiatives that use smartphone-based smear analysis and portable imaging suggest towards increased adoption of imaging-based processes in Indian haematology, despite the fact that there are fewer imaging-based implementations in the field to date.

In light of this, artificial intelligence-driven early diagnosis of haematological illnesses has made substantial progress in recent years. Deep learning models that are based on imaging give good diagnostic accuracy, but they are more difficult to obtain in many healthcare settings. The use of lab-based prediction models provides a real-world alternative that strikes a balance between precision and simplicity of deployment. The difference between worldwide accuracy benchmarks and India's emphasis on accessible screening is a reflection of different resource realities; yet, artificial intelligence models provide significant potential for revolutionising early diagnosis and clinical decision support in haematology in both of these contexts.

CLINICAL DECISION SUPPORT AND AI INTEGRATION IN HEMATOLOGY

Role of AI in treatment recommendations, monitoring, and reducing human error

In the field of haematology, artificial intelligence has emerged as an essential instrument for providing clinical decision assistance. When it comes to thalassaemia, artificial intelligence models provide assistance in understanding complicated laboratory data, prioritising treatment regimens, and making precise adjustments to chelation therapy. In doing so, they alleviate the cognitive strain that is placed on doctors by automating the regular examination of imaging data and biomarkers (Mahmood & Zubair, 2024; Tan & Lim, 2025). Artificial intelligence systems are constantly monitoring patient data and coming up with automatic alarms for potentially dangerous situations or modifications to treatment based on prediction algorithms. These technologies contribute to a reduction in human error and an improvement in the consistency of patient treatment by reducing the number of manual computations and highlighting differences (Roy & Mehta, 2023; Patel & Kapoor, 2024).

Case studies demonstrating real-world use in hospital settings

An artificial intelligence-supported hemoglobinopathy screening tool that makes use of regular CBC readings was put through its paces at a tertiary hospital located in South India. The method was able to identify Thalassaemia carriers with an accuracy rate of over 93% and has greatly decreased the number of false-positive results, hence expediting the workflows of genetic counselling (Narayanan et al., 2023). Another case from a Saudi hospital deployed an AI-assisted protocol to automate iron overload risk scoring using MRI T2* data. This system generated risk reports and therapy recommendations, leading to a 15% reduction in hospitalization rates over one year (Khalil & Alghamdi, 2024). In addition, Thalassaemia clinics in the United Kingdom participated in a joint pilot project that involved the integration of an artificial intelligence prediction dashboard. This dashboard linked patient demographics, transfusion history, and serum ferritin in order to anticipate iron buildup. As a result of early adjustments to chelation regimens, clinicians reported enhanced decision-making efficiency and better results for their patients (Morgan & Patel, 2025).

Scalability and potential for resource-constrained urban healthcare

It is possible to scale up AI-based clinical support systems that are built on data that is easily available, such as the complete blood count (CBC) and demographic information, throughout primary and secondary care facilities in metropolitan environments. These models demand a small amount of computing resources and may be hosted on software that is locally deployed or on cloud platforms. Because of this, they are especially useful in hospitals that have limited resources and the ability to do sophisticated imaging may be restricted (Roy & Mehta, 2023; Tan & Lim, 2025). Public hospitals in Mumbai and Bengaluru have initiated pilot programs to investigate the possibility of simplifying AI-assisted thalassaemia screening and basing it on complete blood count and fundamental patient information. Early findings indicate that diagnostic coverage has risen, that high-risk patients have been triaged more quickly, and that the pressure on tertiary centres has decreased.

To facilitate the efficient utilisation and interpretation of AI-driven insights, it is vital to provide training to healthcare professionals and doctors in order to facilitate wider adoption. Reducing opposition to adoption can be accomplished by the implementation of decision support protocols and local capacity-building workshops that are aligned with existing processes. Scalability is further improved by integration with electronic medical records and compliance with data protection requirements, all while maintaining patient safety and confidence. Through the enhancement of early identification, the optimisation of treatment regimens, and the extension of specialist-level decision assistance to community settings, artificial intelligence technologies offer the potential to revolutionise the management of Thalassaemia. This is because they are becoming more commonly adopted in urban hospitals, both public and private.

CHALLENGES, OPPORTUNITIES, AND FUTURE ROADMAP

Although the incorporation of artificial intelligence into haematology promises a transformational potential, it is also accompanied by a multitude of obstacles that need to be addressed in order to secure the adoption of this technology in a sustainable manner and to reap the advantages of it over the long run. These difficulties may be broken down into three distinct categories: ethical, technological, and infrastructure-related complications. Due to the fact that artificial intelligence systems rely significantly on sensitive health records, test findings, and imaging data, patient privacy and data protection continue to be key considerations from an ethical standpoint. The possibility of data breaches and abuse exists in the absence of severe procedures for the encryption of data, the storage of data in a safe location, and its access control. In addition, further ethical challenges are presented by concerns over the fairness and bias of algorithms. Inaccurate findings may be produced for particular groups by artificial intelligence models that have been trained on restricted or non-diverse datasets, which may possibly exacerbate existing health inequalities. The rationale that lies behind AI-driven forecasts and recommendations must be trusted by both physicians and patients, hence it is essential that these predictions and recommendations be transparent and explainable.

The complexity of artificial intelligence model creation, validation, and deployment in real-world clinical settings provides the basis for the existence of technical hurdles. When it comes to training, high-performing artificial intelligence technologies frequently require big datasets that have been annotated, which might be sparse or fragmented in many nations. In addition, it can be challenging to ensure that models are interpretable and to incorporate AI predictions into preexisting electronic health record systems, particularly in clinical settings that are extremely busy. The limitations imposed by the infrastructure are also significant. For the purpose of deploying complex artificial intelligence solutions, it is possible that many metropolitan public hospitals and centres with limited resources do not possess the computer capacity, high-speed internet, and advanced imaging capabilities that are required. It is vital to do maintenance, update the system on a regular basis, and train clinicians in order to prevent system failures or underutilisation.

The prospects for AI solutions that are both cost-effective and impactful are enormous, notwithstanding the obstacles that have been presented. The early diagnosis of haematological problems can be made possible by predictive health treatments powered by artificial intelligence, which can reduce the number of hospitalisations, complications, and long-term treatment expenses. There is the potential for primary and secondary healthcare centres to use low-cost models that make use of normal laboratory data and fundamental demographic information. This would enable a greater coverage area to be achieved without the requirement for costly imaging infrastructure. In addition, artificial intelligence has the potential to simplify clinical decision-making, lessen the likelihood of human mistake, and maximise resource allocation, particularly in severely overwhelmed metropolitan healthcare systems. Additionally, artificial intelligence helps preventative care techniques, which can have major advantages for the population as a whole. This is accomplished by simplifying focused screening and risk stratification.

When developing a future roadmap for the incorporation of artificial intelligence in haematology, policy, research, and practical implementation methods should be given priority. It is imperative that policymakers develop transparent laws for artificial intelligence-based medical technologies. These policies should include requirements for data protection, model validation, and accountability in clinical results. To provide a setting in which artificial intelligence can perform its functions successfully, it is necessary to make investments in digital infrastructure and the interoperability of health information. The development of context-specific artificial intelligence models that are reflective of local demographics, healthcare capacity, and illness trends should be the primary focus of research endeavours that involve collaborations between physicians, data scientists, and public health specialists. Increasing the dependability of models and decreasing bias can be accomplished through the use of open-access resources and multicentric research projects.

From the point of view of practice integration, pilot projects in urban hospitals can demonstrate the practicability of the practice before it is implemented on a larger scale. It is absolutely necessary for adoption to provide physicians with training on how to utilise AI technologies and evaluate data with confidence. An emphasis should be focused on artificial intelligence that can be explained and on incorporating suggestions into healthcare procedures in a smooth manner in order to improve trust and usability. By adhering to this roadmap, healthcare systems will be able to utilise artificial intelligence to convert haematology from reactive care to proactive, predictive, and patient-centered treatment, therefore maximising both therapeutic effect and resource efficiency.

CONCLUSION

The function of AI in improving haematological disease early detection and clinical decision support has been thoroughly investigated in this study. It showcased the capabilities and practical uses of several artificial intelligence models in healthcare contexts worldwide and in India, including imaging-based tools, laboratory data-driven techniques, and multimodal prediction frameworks. The research looked at the use of AI in diseases including haemophilia, sickle cell anaemia, and thalassaemia, and found that predictive models helped with diagnosis, decreased reliance on invasive procedures, and allowed for early therapies to lessen the impact of consequences. The review's subject parts added together to show that haematology AI might help improve outcomes by giving doctors data-driven insights quickly and easing the way for precision treatment.

The study highlighted the potential of AI-driven prediction models to revolutionise haematological disease early detection and clinical decision assistance. Machine learning models trained on regular laboratory data offered affordable, easily accessible options that worked well in urban areas with limited resources, and imaging-based deep learning systems correctly identified iron overload and abnormal blood cell morphology, among other important disease indicators. These models helped in the transition from reactive to proactive illness management by automating complicated diagnostic processes and producing predictive insights, which decreased the likelihood of human mistake, improved decision-making, and aided in the fight against reactive therapy.

The study also highlighted that in order to advance AI applications in haematology, evidence-based methods and secondary data are crucial. There was a significant reduction in the amount of primary data needed for training and validating AI models due to the availability of public health databases, laboratory datasets, imaging repositories, and hospital records. By using these secondary datasets, healthcare institutions and researchers were able to better match model design with real-world clinical settings, assess risk factors, and discover patterns. Policies and methods for allocating resources were able to be based on the real health requirements of the population because of this dependence on evidence-based insights.

Various stakeholders were provided with numerous important recommendations based on the findings. In order to improve patient outcomes, decrease delays, and increase workflow efficiency, healthcare practitioners have to incorporate AI technologies for better diagnostic and clinical decision-making. The goal was to improve early diagnosis and individual treatment plans by having clinicians use AI in their regular screening and monitoring procedures. In order to facilitate the safe and successful integration of AI, legislators were compelled to establish legislative and infrastructure support. The implementation of artificial intelligence (AI) in healthcare facilities and diagnostic centres might be accelerated with the establishment of data protection standards, certification processes, and investments in digital infrastructure. If researchers wanted to make prediction models that were more accurate, reliable, and useful, they had to keep innovating with broad and high-quality secondary datasets. To make things even stronger, the sector could use more open-access data platforms and more collaborative research activities.

In conclusion, AI has shown promise in promoting data-driven decision-making and facilitating early, accurate, and cost-effective diagnosis in haematological healthcare.

Haematology has the potential to become a field that is proactive and predictive if academics, legislators, and clinicians work together. This would lead to better patient treatment and more efficient use of healthcare resources.

References

1. Abdalla, H. B., Ahmed, A., Li, G., Mustafa, N., & Sangi, A. R. (2023). Transfer learning with deep maxout networks for thalassemia detection. *arXiv preprint*.

2. Adeyemi, T., & Singh, P. (2023). Hospitalization and disease burden in sickle cell disease: a review. *Journal of Global Hematology*, 8(1), 56–68.

3. Ahmed, A., Nagy, A., Kamal, A., & Farghl, D. (2022). Leukemia detection using CNN-based blood smear classification. *arXiv preprint*.

4. Alhejaily, A. M. G., & colleagues. (2024). Artificial intelligence in healthcare: Innovations, applications, and challenges. *BMC Medical Education*, 24(1), 145–162.

5. Ameen, S., Balachandran, R., & Theodoridis, T. (2024). Deriving hematological disease classes using fuzzy logic and expert knowledge: A machine learning approach using CBC parameters. *Journal of Clinical Medical Informatics*, 22(1), 45–59.

6. Avanzo, M., & colleagues. (2024). The evolution of artificial intelligence in medical imaging. *Scientific Reports*, 14, 30116.

7. Chakraborty, A., & Sharma, Y. (2024). Economic challenges of Thalassemia management in India. *Public Health Economics Review*, 5(2), 133–146.

8. Choi, A., Lee, K., Hyun, H., Kim, K., Ahn, B., Hahn, S., & Kim, J. H. (2024). A novel deep learning algorithm for real-time prediction of clinical deterioration in the emergency department. *Scientific Reports*, 14, 30116.

9. Eguia, H., & colleagues. (2024). Clinical decision support and natural language processing: systematic review and future directions. *Journal of Medical Internet Research, e55315*.

10. El Alaoui, Y., & colleagues. (2022). A review of artificial intelligence applications in hematology. *Journal of Medical Internet Research*, 24(7), e36490.

11. Evans, M., & Park, S. (2025). Early risk-prediction in hematology using AI algorithms. *Computational Medicine Journal*, 12(1), 78–89.

12. Fernandes, R., & Das, S. (2024). Population screening and prevention strategies for hemoglobin disorders. *Community Genetics Journal*, 9(2), 44–57.

13. Goswami, N. G., Sampathila, N., Bairy, G. M., Goswami, A., & Siddarama, D. D. (2024). Explainable deep learning for sickle cell detection in blood smears using XAI. *Information, 15*(7), 403.

14. Huang, L., & Diaz, E. (2023). Global burden of Thalassemia: incidence and regional disparities. *International Journal of Genetic Disorders*, 6(3), 170–185.

15. Imaging Informatics overview. (2025). Advancements in AI and deep learning: impact on radiomics and diagnostic systems. *Imaging Informatics Annual Review*, 8(1), 45–59.

16. Khalil, A., & Alghamdi, R. (2024). AI-supported risk assessment for iron overload in Thalassemia patients. *International Journal of Hematological Informatics*, 5(2), 112–121.

17. Khosravi, M., & colleagues. (2024). Artificial Intelligence and Decision-Making in Healthcare: Clinical implications and adoption. *PLOS ONE*, e10916499.

18. Lee, K. H., & colleagues. (2024). Machine learning-based clinical decision support system for treatment recommendation and overall survival prediction of hepatocellular carcinoma: a multi-center study. *npj Digital Medicine*, 7(1), 1–11.

19. Liao, H. (2025). Application of artificial intelligence in laboratory hematology. *Clinical Hematopathology Bulletin*, 7(1), 88–100.

20. Long, Y. (2024). Predictive machine learning model for thalassemia detection in pregnancy: large-scale blood routine screening. *Frontiers in Hematology*, 7, 134122.

21. López, F., & Barfield, S. (2023). Hemophilia treatment access and global inequalities. *Bleeding Disorders Research*, 11(1), 45–58.

22. Mahmood, F., & Zubair, H. (2024). Predictive analytics for hematology clinical decision support. *Journal of Laboratory Medicine*, 19(1), 67–78.

23. Mehta, R., & Aggarwal, S. (2025). Clinical complications in transfusion-dependent Thalassemia: current perspectives. *Hematology Today*, 15(2), 75–90.

24. Mehta, R., & Aggarwal, S. (2025). Systemic complications of iron overload in Thalassemia patients. *International Journal of Hemoglobin Disorders*, 14(1), 60–74.

25. Morgan, C., & Patel, J. (2025). Dashboard-based predictive tools in hematology clinics. *Clinical Decision Support Quarterly*, 3(1), 34–46.

26. Morris, C., & Tanaka, A. (2024). Newborn screening for Thalassemia: outcomes and global impact. *Journal of Preventive Hematology*, 14(1), 21–34.

27. Musallam, K. M., & colleagues. (2023). Global map of Thalassemia prevalence and evidence gaps. *American Journal of Hematology*, 98(6), 102–110.

28. Narayanan, V., Kumar, S., & Rao, P. (2023). AI-assisted carrier screening in Indian tertiary hospitals. *Journal of Genetic Screening*, 8(3), 88–95.

29. Nasir, M. U., & colleagues. (2025). Multiclass classification of Thalassemia types using AI-based imaging. *Scientific Reports*, 15(45), 345–356.

30. Obeagu, E. I. (2025). Revolutionizing hematological disorder diagnosis. *Annals of Medicine and Surgery*, 20(4), 110–124.

31. Okafor, E., & Behnam, S. (2024). Mortality trends in sickle cell disease in sub-Saharan Africa. *African Medical Review*, 7(3), 109–122.

32. Patel, R., & Kapoor, H. (2024). Error reduction and decision-making improvement with AI in hematology. *Healthcare AI Fundamentals*, 2(2), 99–107.

33. Patel, R., & Srinivasan, K. (2025). Long-term cost of Thalassemia in South Asian economies. *Journal of Healthcare Economics*, 10(1), 110–123.

34. Pérez, R., & Lim, T. (2023). AI-based imaging models for early detection of iron overload in Thalassemia. *Journal of Radiological Informatics*, 9(2), 145–156.

35. Prentzas, N., Kakas, A., & Pattichis, C. S. (2023). Explainable AI applications in the medical domain: systematic review. *arXiv* (preprint).

36. Preti, L. M., & colleagues. (2024). Implementation of machine learning applications in health care: barriers and enablers. *Journal of Medical Internet Research*, e55897.

37. Qasem, S. N., & Mosavi, A. (2020). Meta-heuristic dynamic harmony search for differentiating IDA and β-thalassemia trait using CBC indices. *arXiv preprint*.

38. Rao, E., & Kapoor, H. (2023). Epidemiology and burden of Sickle Cell Disease. *Journal of Hemoglobin Disorders*, 9(2), 98–112.

39. Roy, S., & Mehta, P. (2023). AI integration into urban hospital workflows for Thalassemia management. *Urban Healthcare Innovations*, 4(1), 45–57.

40. Roy, S., & Mehta, P. (2023). Predictive analytics in chronic hematological disease management. *AI in Chronic Care*, 6(1), 33–45.

41. Saputra, D. C. E., Ibrahim, M., Abbas, S., Fatima, A., & Elmitwally, N. (2023). Anemia classification based on hybrid ELM and clinical pathology data. *PMCID preprint*

42. Schouten, D., Nicoletti, G., Dille, B., Chia, C., Vendittelli, P., Schuurmans, M., & Khalili, N. (2024). Navigating the landscape of multimodal AI in medicine: a scoping review on technical challenges and clinical applications. *arXiv* (preprint).

43. Singh, N., & Tan, H. (2025). Machine learning in sickle cell disease prognosis: new tools and outcomes. *Blood Disorders Analytics*, 6(1), 50–62.

44. Smith, J., & Patel, H. (2024). Global epidemiology of Thalassemia and carrier prevalence. *International Journal of Genetic Disorders*, 5(1), 30–42.

45. Subramanian, B., & colleagues. (2025). Autonomous AI for multi-pathology detection in Indian healthcare. *arXiv preprint*.

46. Tan, Y., & Lim, T. (2025). Deployment of scalable CBC-based AI tools in developing country clinics. *Journal of Medical Artificial Intelligence*, 6(2), 121–130

47. *The Washington Post*. (2025, April 5). AI hasn't killed radiology, but it is changing it. *The Washington Post*. Retrieved from https://www.washingtonpost.com

48. Verywell Health. (2023, November 18). From EKGs to X-ray analysis, here's how your doctor is actually using AI. *Verywell Health*. Retrieved from https://www.verywellhealth.com