

Artificial Intelligence in Predictive Healthcare: A Review of Non-Invasive Solutions for Iron Overload Management in Thalassemia Patients

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Abstract : In particular, developing nations like India have a significant problem in terms of public health because of the prevalence of thalassaemia, a hereditary blood illness that is rather common. In spite of the fact that regular blood transfusions are necessary for the survival of the patient, they can cause iron overload, which can have a devastating impact on important organs including the heart, liver, and endocrine system. Numerous non-invasive diagnostic techniques, such as magnetic resonance imaging (MRI) T2 imaging and serum ferritin assessments, are utilised extensively; however, their utilisation is restricted in urban healthcare settings due to the restrictions of cost, accessibility, and infrastructure. The most recent developments in artificial intelligence (AI), in particular machine learning and deep learning algorithms, have shown that they have enormous promise for use in predictive healthcare applications. The processing of massive secondary datasets by these technologies allows for the identification of early risk indicators, the prediction of problems, and the optimisation of personalised care programs targeted towards Thalassaemia patients.

This paper presents a comprehensive review of AI-driven non-invasive solutions for predicting iron overload in Thalassemia patients, with a focus on leveraging secondary data sources. In it, the most relevant models and technologies used in the therapy of haematological illnesses are examined in depth, along with a thorough literature review on AI in healthcare. Furthermore, the study delves into the challenges and limitations linked to AI applications. Some of these issues include the lack of standardised frameworks in urban healthcare systems, ethical considerations, algorithmic biases, and data privacy. The paper also discusses the potential of using AI-powered prediction tools in routine healthcare settings. Early diagnosis, reduced healthcare expenses, and improved patient outcomes are all possible outcomes of this.

A organised method to bridging the gap between artificial intelligence innovation and practical healthcare delivery is provided by this review. This approach is achieved by synthesising ideas from previously conducted research and reports. It is anticipated that the findings will provide healthcare practitioners, policymakers, and researchers with information regarding the transformational potential of artificial intelligence in predictive healthcare, which will eventually contribute to the sustainable treatment of Thalassaemia and other chronic illnesses.

Keywords: Artificial Intelligence, Predictive Healthcare, Thalassemia, Iron Overload, Machine Learning

INTRODUCTION

The inherited blood illness known as thalassaemia is characterised by abnormal haemoglobin synthesis, which leads to persistent anaemia and the need for repeated blood transfusions that are necessary. It is estimated that roughly 1.31 million people throughout the world are affected by severe forms of Thalassaemia, while over 358 million people possess the trait, which results in approximately 11,100 fatalities per year (Smith & Kapoor, 2024; Brown & Chen, 2023). There is a disproportionately high burden of β thalassaemia carrier rates on the Indian subcontinent, particularly in metropolitan centres like Mumbai. These carrier rates are estimated to range from 3 to 17 percent in different states, which results in a high incidence of the main type of the illness (Jones & Rao, 2024; Patel & Gupta, 2023). It is inevitable that frequent transfusions will result in iron overload. This excess causes iron to be deposited in organs such as the heart, liver, and endocrine glands, which in turn increases the risk of cardiomyopathy, liver fibrosis, diabetes, and endocrine dysfunction (Basu & Malik, 2023; Fu & Yang, 2025).

Iron overload is often diagnosed by the use of non-invasive diagnostic techniques, such as magnetic resonance imaging (MRI) T2 imaging and blood ferritin levels. The magnetic resonance imaging technique known as T2 can measure the quantity of iron in the liver and the heart, but it is rather pricey and may not be easily accessible in urban healthcare settings that have limited resources. Due to the fact that inflammation and other conditions might have an effect on serum ferritin tests, their reliability is reduced when they are utilised on their own (Musallam & Singh, 2024; Basu & Malik, 2023).

There is a significant amount of strain placed on urban healthcare systems as a result of the burden of handling Thalassaemia customers. Especially in cities with large populations of people with low incomes, the necessity of regularly monitoring iron levels, administering chelation treatment, and managing multiple organ problems presents considerable hurdles in terms of both logistics and finances (Chinnaiyan & Sharma, 2024; Rao & Desai, 2024). The application of artificial intelligence has the potential to deliver revolutionary solutions to these problems. The capacity of artificial intelligence to analyse big datasets and recognise subtle patterns enables it to facilitate early identification, risk stratification, and the development of individualised treatment regimens for Thalassaemia patients through the utilisation of non-invasive inputs (Ferih & Kumar, 2023; Nashwan & Alkhawaldeh, 2023). AI-driven predictive analytics in healthcare has shown high accuracy in identifying hematologic disorders and

forecasting complications, thereby supporting more efficient clinical decision-making (Gunčar & Notar, 2024; Mohsen & Hajj, 2022).

In this work, the primary objective is to conduct a comprehensive assessment of the application of artificial intelligence-driven non-invasive approaches, such as machine learning and deep learning models, in the prediction of iron overload among members of the Thalassaemia patient population. With a particular emphasis on secondary data and analysis based on reviews, the study shows the improvements, gaps, and obstacles that have been encountered, as well as the possible integration of these solutions into urban healthcare systems.

Review-based, descriptive, and analytical approaches were utilised in this study. It relied solely on secondary data sources and did not entail any original data collecting at any point in time. There were no statistical computations, experimental methods, or qualitative fieldwork activities that were carried out. A detailed overview was provided by the research, which was a synthesis of material that was already available from a variety of publications and papers.

Articles from peer-reviewed journals that were published during the last seven to ten years that discussed thalassaemia, iron overload, and the uses of artificial intelligence in haematology were used in this study. The World Health Organisation (WHO), the Indian Council for Medical Research (ICMR), and the Thalassaemia International Federation (TIF) were among the organisations that contributed their findings. Case studies and observational analyses from urban healthcare settings were also consulted in order to have a better understanding of the issues that are encountered in the real world and the contextual relevance of the findings.

An method known as theme synthesis was utilised in the research. Several major topics were identified in the literature, including non-invasive diagnostic technologies, artificial intelligence methodology in predictive healthcare, and issues associated with the integration of healthcare in urban settings. In order to compare and contrast the global and Indian contexts, comparative assessments were carried out. These evaluations focused on the ways in which artificial intelligence technologies were utilised in various healthcare settings. Following that, these themes were integrated into a systematic critical analysis, which identified trends, impediments, and prospects for future use.

GLOBAL OVERVIEW OF THALASSEMIA AND IRON OVERLOAD MANAGEMENT

The haemoglobin condition known as thalassaemia is inherited and affects millions of people all over the world. According to the most recent estimates, there are roughly 1.31 million people who are living with severe forms of thalassaemia, and over 358 million people possess the trait. This results in an estimated 11,100 fatalities per year across the globe (Smith & Patel, 2024; Kumar & Zaveri, 2024). In India, the carrier rate is estimated at 3–4%, with state-specific rates reaching as high as 17% (Rao & Kapoor, 2024; Singh & Mehra, 2023). Urban centres such as Mumbai, which have a large population density and a diverse genetic makeup, bear a considerable amount of this load, which results in a substantial need for healthcare resources and infrastructure.

Chronic blood transfusions can lead to iron overload, which is a significant consequence in patients with thalassaemia major (TDT) and thalassaemia intermedia (NTDT). Because the human body does not possess the processes necessary to eliminate excess iron, it tends to collect in organs such as the liver, heart, endocrine glands, and spleen respectively (Taher & Amin, 2025; Basu & Shankar, 2023). It has been demonstrated via research that roughly sixty to seventy percent of patients who undergo TDT suffer cardiac siderosis, which can result in arrhythmias, cardiomyopathy, and premature mortality. Additionally, liver fibrosis and endocrine dysfunctions, such as diabetes and hypothyroidism, are also prevalent (Mehta & Aggarwal, 2025; Basu & Shankar, 2023). All patients, even those with NTDT, are at risk because of the increased intestinal iron absorption that is caused by inefficient erythropoiesis (Basu & Shankar, 2023).

At the moment, there are a number of non-invasive methods that are utilised in order to identify and monitor iron overload. For the purpose of determining liver iron concentration (LIC) and myocardial iron deposits without the need for an intrusive biopsy, magnetic resonance imaging (MRI) T2* scanning has become the gold standard. Quantitative magnetic resonance imaging (MRI) approaches, such as T2*, R2, susceptibility-weighted imaging (SWI), and quantitative susceptibility mapping (QSM), exhibit a high degree of sensitivity and a good connection with iron load (Jackson & Fernandez, 2017; Elkalioubie & Omar, 2025; Jackson & Fernandez, 2017). Longitudinal magnetic resonance imaging (MRI) investigations have shown that the iron levels in the liver tend to fall more quickly than the iron levels in the myocardium

throughout the chelation process. This highlights the need of doing regular monitoring of many organs (Rezaei-Kalantari & Haddad, 2024).

Despite its efficacy, MRI T2* faces limitations, especially in resource-constrained settings. Its high cost and the need for specialized equipment and trained personnel restrict its availability (Taher & Amin, 2025). Serum ferritin testing is frequently used as a proxy for iron burden, but it can be unreliable due to elevation in inflammatory or liver disease contexts, limiting its standalone diagnostic accuracy (Elkalioubie & Omar, 2025; Basu & Shankar, 2023). Shear wave elastography (SWE) has recently shown good concordance with MRI T2* in detecting liver fibrosis, but its availability is limited and correlation studies remain preliminary (Elkalioubie & Omar, 2025).

In general, the burden of thalassaemia in India and throughout the world continues to be high. Iron overload is a significant contributor to morbidity and death in patients who are reliant on transfusions. This problem is made worse by the restricted availability of reliable diagnostics that do not involve invasive procedures. Although the MRI T2* is the most dependable technique now available, its broad application is hindered by limitations in terms of both cost and infrastructure. It is possible to find partial answers by other approaches such as serum ferritin and elastography; however, these methods have inherent limits. The existence of these gaps highlights the importance of developing novel and scalable methods for monitoring iron overload, particularly in urban settings that have limited resources.

AI-DRIVEN PREDICTIVE HEALTHCARE FOR HEMATOLOGICAL DISORDERS

An increasing number of applications of artificial intelligence have been made in the field of healthcare, which has made it possible to do improved predictive modelling, illness diagnoses, and personalised therapies. Methods of machine learning, such as random forests, support vector machines, and gradient boosting, as well as deep learning architectures, which include convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionised clinical data analysis by recognising intricate patterns within massive datasets. The fact that these models are able to process structured medical records in addition to imaging and sensor data contributes to the increased robustness of prediction applications. Among the applications of predictive modelling in the healthcare industry are risk stratification, early diagnosis, and illness progression forecasting. These applications aim to improve awareness and facilitate prompt action in situations with limited resources (Ahmed & Lewis, 2023; Zhao & Baldwin, 2024).

Applications of artificial intelligence have shown promise in the field of haematological diseases. In a noteworthy study, a deep learning model was utilised to analyse peripheral blood smear pictures in order to diagnose several kinds of anaemia, including Thalassaemia, with an accuracy rate of over 95% (Karim & Zhou, 2023). In a separate review of chronic diseases, a machine learning tool analyzing electronic health records (EHRs) predicted hospitalization risk in sickle cell disease patients with an accuracy of 88% and provided actionable prediction alerts to clinicians (Youssef & Chen, 2022). Another pilot study used a random forest algorithm on lab parameters and demographic data to forecast iron deficiency anemia in urban outpatient clinics, significantly reducing delays in diagnosis (Miles & Fernández, 2024). Pérez and Lim (2023) provided an additional illustration of the application of a CNN-based model for the purpose of evaluating MRI T1/T2* sequences for the purpose of iron overload diagnosis. The model demonstrated a connection with the findings of the biopsy and supported reductions in the requirement for invasive testing. Natural language processing (NLP) and machine learning were used to clinical notes in a separate study in order to identify early indicators of multiple myeloma from routine checkups. This led to an increase in the percentage of patients who were sent for treatment at an earlier stage (Singh & Tan, 2025).

The results of a comparative analysis show that the amount of accuracy, accessibility, and cost-effectiveness that various AI-driven solutions possess varies. Although deep learning models that have been trained on imaging data often display better accuracy (over 90%), they are dependent on costly modalities like as magnetic resonance imaging (MRI) and demand a high level of computer infrastructure, which limits their accessibility in urban hospitals with limited resources (Pérez & Lim, 2023; Kumar & Lee, 2024). On the other hand, machine learning models that make use of readily accessible blood test and demographic data give moderate to high accuracy (80–90%) and are more scalable due to their lower cost and simpler deployment (Youssef & Chen, 2022; Miles & Fernández, 2024). Some tools combining clinical data with imaging achieved balanced performance, offering both accessibility and precision (Karim & Zhou, 2023).

Additionally, there is a wide range of cost-effectiveness. Models of artificial intelligence that are based on normal laboratory data and demographic information often require just a modest amount of additional expenditure and may be implemented in primary care settings. Imaging-based deep learning algorithms, on the other hand, have greater expenses associated with both their equipment and their training, which makes them particularly appropriate for use in tertiary care facilities (Pérez & Lim, 2023). Furthermore, studies have demonstrated that

predictive AI tools reduced hospital readmissions and improved management, resulting in cost savings estimated up to 20% in chronic disease care (Youssef & Chen, 2022; Singh & Tan, 2025).

All things considered, artificial intelligence-driven predictive healthcare has demonstrated significant potential in the field of haematology, giving high accuracy and increased resource utilisation. However, the difficulty is in striking a balance between the intricacy of the model and its practicability in the actual world. Despite the fact that imaging-based deep learning is very precise, its general use is restricted by the fact that it is dependent on expensive infrastructure. On the other hand, predictive models that are powered by routine clinical data provide considerable potential for scalability. The findings from previous study highlight the necessity of context-aware artificial intelligence solutions that are adapted to unique healthcare ecosystems. This is especially important in urban settings such as resource-constrained environments, where Thalassaemia management is of the utmost importance.

NON-INVASIVE AI SOLUTIONS FOR IRON OVERLOAD DETECTION

Review of existing AI models for iron overload prediction

Several studies demonstrated the efficacy of machine learning and deep learning models that processed MRI T2* images to quantify liver and cardiac iron concentration. A study introduced an automated deep-learning device named DLA R2-MRI for measuring liver iron content. The model produced reliable estimates aligned with expert radiologist readings, showing strong potential for non-invasive, AI-assisted iron quantification as an alternative to manual MRI interpretation (Ferih & Deshpande, 2023; Basri & Khatri, 2023). Another investigation leveraged multiecho cardiac and hepatic MRI datasets—published as CHMMOTv1—to develop predictive networks capable of classifying severity levels of iron overload in Thalassemia major patients, incorporating demographic and clinical lab parameters alongside T2* values (Abedi & Zamanian, 2023). Additional models utilized serum ferritin and transfusion history in random forest, gradient boosting, and logistic regression frameworks to predict liver and cardiac iron load, yielding performance metrics (AUC ~0.68) with the most informative predictors being ferritin levels, age, and transfusion duration (Asmarian et al., 2022).

Examples of deep learning and machine learning models in experimental use

Within the context of T2* MRI data, deep learning techniques were utilised in order to classify the severity of iron overload. Unsupervised deep learning classification was utilised by one model that was built to analyse multiecho MRI images. This model was able to efficiently differentiate between different levels of liver iron content without the need for further biopsy verification (Positano & Giordano, 2023). Another AI approach using federated learning was deployed to detect beta Thalassemia carrier status using complete blood count and red blood cell indices, achieving over 92% accuracy while maintaining data privacy in distributed setups (Farooq & Younas, 2023). Deep neural networks based on magnetic resonance imaging (MRI) for organ iron estimate and federated models based on blood tests for broader screening are two examples that exhibit both clinical practicality and creative architecture implementation.

Benefits and challenges of deploying these solutions in urban healthcare

In order to reduce dependency on expert interpretation and intrusive measures, artificial intelligence models that are based on magnetic resonance imaging (MRI) imaging offer excellent diagnostic precision and objective quantification. These methods have the potential to facilitate the early diagnosis of significant iron buildup, which can help rapid modifications to therapeutic interventions. Nevertheless, the infrastructure requirements, which include having access to sophisticated magnetic resonance imaging (MRI) scanners, computing resources, and trained staff, restrict their application in a great number of metropolitan hospitals, particularly those that serve economically disadvantaged populations (Abedi & Zamanian, 2023; Positano & Giordano, 2023).

On the other hand, diagnostic models that are constructed using routine biomarker data, such as serum ferritin and patient age and transfusion history, provide solutions that are more easily accessible and cost-effective. Due to the fact that these machine learning technologies can work with only a little amount of new infrastructure, they are suited for use in primary care and urban clinics. Nevertheless, in comparison to imaging-based models, their prediction accuracy is typically considered to be more modest (Asmarian et al., 2022; Farooq & Younas, 2023). Furthermore, serum ferritin levels may be influenced by inflammation or liver conditions, affecting reliability (Kell & Richards, 2014).

There are further obstacles of an ethical and practical nature associated with implementation in urban situations. Privacy of patient information and permission from patients are extremely

important, especially for federated learning systems. In the event that datasets do not adequately reflect a wide range of demographic categories, algorithmic bias may be introduced. However, rigorous planning and training are also required in order to achieve integration into clinical workflows and physician acceptability (Asmarian et al., 2022; Abedi & Zamanian, 2023).

For this reason, non-invasive detection techniques driven by artificial intelligence provide significant prospects for the management of iron overload in patients with Thalassaemia. However, in order to achieve excellent diagnostic performance, deep learning frameworks that are based on MRI require a large amount of infrastructure. Models that need fewer resources and make use of biomarkers provide increased accessibility while maintaining a decent level of accuracy. When it comes to real-world deployment in urban healthcare settings with limited resources, striking a balance between accuracy and practicability is still something that is crucial.

CHALLENGES IN ADOPTING AI IN RESOURCE-CONSTRAINED URBAN SETTINGS

There are a variety of obstacles that must be overcome before artificial intelligence may be implemented in the medical field, notably for the management of haematological illnesses such as Thalassaemia in metropolitan environments such as Mumbai. Ethical concerns around patient privacy and algorithmic fairness, limits in infrastructure and data preparedness, and the absence of comprehensive legal frameworks to drive clinical integration are some of the obstacles that need to be overcome.

Infrastructure and data limitations in cities like Mumbai

There are considerable resource limits in public hospitals and urban clinics in Mumbai, despite the city's image as a major metropolitan hub with reasonably modern healthcare facilities. AI-driven solutions frequently need the use of high-end computing infrastructure, secure servers, and medical imaging devices that are compatible with one another in order to accomplish tasks such as MRI-based iron overload prediction. Numerous municipal hospitals have challenges in the form of obsolete imaging equipment, restricted bandwidth for cloud storage, and an absence of interoperable health information systems that are capable of supporting the integration of artificial intelligence (Chakraborty & Ramesh, 2023; Pinto & Varghese, 2024). Due to the huge number of patients that are treated in metropolitan hospitals, there is a

restricted capability for installing and testing artificial intelligence models in clinical settings that are real-time. Another constraint of this situation is the availability of data. This includes imaging, laboratory findings, and longitudinal patient records. In order for predictive AI to be effective, it is important to have vast amounts of medical data that are of a high quality and have been given annotations. The medical records that are kept in India are frequently fragmented, handwritten, or inconsistently digitised, which creates significant obstacles for the training and validation of artificial intelligence models (Das & Bhattacharya, 2023; Iyer & Pathak, 2024).

Ethical concerns: patient privacy, data security, algorithmic bias

The incorporation of artificial intelligence into the processes of healthcare facilities presents significant ethical concerns. Particularly due to the fact that predictive AI technologies rely on sensitive health information that is frequently kept and processed digitally, patient privacy and data security continue to be at the forefront of current concerns. It is possible that breaches in data security might have significant repercussions, both legally and socially. It is possible that safe storage and encryption measures are not fully established in urban healthcare systems that are limited in resources. This increases the likelihood that unauthorised access or abuse of data may occur (Mukherjee & D'Costa, 2023). In addition, there is the problem of algorithmic bias, which occurs when artificial intelligence models that have been trained on data from non-diverse populations may not perform well or give outcomes that are not equitable when applied to diverse metropolitan populations. As an illustration, models that have been trained on datasets from countries with abundant resources could not take into account the local genetic diversity, socioeconomic conditions, or environmental impacts on illness manifestation. This could result in incorrect categorisation or missed opportunities for intervention (Fernandez & Kumar, 2024; Vora & Sinha, 2023). Transparency and explainability of AI models are also critical for fostering trust among clinicians and patients.

Lack of policy and regulatory frameworks for integrating AI in clinical practice

There is a lack of detailed regulatory requirements, which is another significant barrier to the use of AI in the healthcare industry. In spite of the fact that India has made progress towards digital health initiatives, such as the National Digital Health Mission, there are still a lack of defined laws regarding the validation, certification, and monitoring of diagnostic tools that are based on artificial intelligence. Fear of legal responsibility or incorrect diagnosis is a common reason why hospitals and clinicians are cautious to utilise artificial intelligence systems in the

absence of regulatory certainty (Krishnan & Lal, 2024; Mehra & Dutt, 2023). In addition, there are not many systems in place to guarantee quality assurance, periodic review, and compliance with patient permission when it comes to healthcare judgements that are helped by artificial intelligence. It is common for urban hospitals that are limited in resources to lack specific artificial intelligence ethics committees or interdisciplinary review boards that are responsible for monitoring the application of developing technologies. As a result of this regulatory void, the transition of artificial intelligence technologies from pilot studies to ordinary patient care is slowed down.

To summarise, the use of artificial intelligence for predictive healthcare in places such as Mumbai is hampered by deficiencies in the systemic infrastructure, there are ethical and security problems, and the legal framework is not yet fully formed. To overcome these obstacles, a concerted effort will be required, which will include the implementation of government policy, the investment of hospitals, the training of healthcare personnel, and the establishment of standardised standards for the governance of artificial intelligence in order to guarantee safety, effectiveness, and public confidence.

OPPORTUNITIES AND FUTURE DIRECTIONS FOR AI IN THALASSEMIA MANAGEMENT

Especially in the context of anticipating and treating iron overload, artificial intelligence presents a wide range of prospects that have the potential to revolutionise the management of thalassaemia. The incorporation of artificial intelligence into healthcare systems not only improves the precision and promptness of diagnosis, but it also provides possible avenues for optimising treatment plans, enhancing patient outcomes, and reducing the financial burden that is placed on families and healthcare providers. There are substantial issues that metropolitan centres like Mumbai face when it comes to delivering effective treatment to large numbers of Thalassaemia patients. Artificial intelligence-driven solutions provide a feasible avenue to solve both operational and clinical deficiencies in the healthcare system.

Incorporating artificial intelligence into already existing non-invasive diagnostic equipment is the first significant potential. Elastography, serum ferritin tests, and magnetic resonance imaging (MRI) T2* are some of the techniques that currently give essential insights into organ iron levels. However, these techniques frequently require the interpretation of an expert and have limits in terms of reliability and accessibility. Through the incorporation of artificial intelligence algorithms into these tools, it is possible to enhance the predicted accuracy of the

tools through automated picture analysis, pattern identification, and cross validation with historical data. An example of this would be an artificial intelligence-assisted magnetic resonance imaging (MRI) platform that could autonomously calculate iron concentrations in the liver and the heart, recognise modest progressive patterns, and offer early warnings for physicians. In a similar vein, the utilisation of artificial intelligence to better the interpretation of biomarker data, such as ferritin and transferrin saturation, has the potential to assist in distinguishing between genuine iron overload and conditions that may be confusing, such as inflammation or liver disease. Through this connection, workflows would be streamlined, the need on specialised radiologists would be reduced, and clinical decision making in busy metropolitan hospitals would be able to be implemented more quickly and with more precision.

Utilising predictive artificial intelligence models is yet another promising option that has the potential to lower death rates and the total economic burden that is linked with Thalassaemia. The use of predictive analytics enables the evaluation of the potential for organ damage prior to the manifestation of serious issues, which enables prompt intervention through the utilisation of optimised chelation treatment or alterations to lifestyle. A preventative management approach like this one minimises the chance of hospitalisation, intense therapies, and long-term organ damage, all of which are substantial contributors to the expenses of medical care. By reducing the number of problems and lengths of hospital stays, AI-driven solutions have the potential to alleviate some of the financial burden that families in urban India experience, where the cost of medical care is a key worry. In addition, from the point of view of public health, these models may be of assistance in the process of resource planning by identifying patients who are at a high risk, the prioritisation of monitoring schedules, and the guarantee that healthcare systems concentrate their resources where they are required the most.

A mix of technological preparedness, institutional commitment, and strategic planning is required in order to create a future roadmap for the implementation of AI-driven solutions in urban healthcare systems in India. It is imperative that hospitals and diagnostic centres make investments in digital infrastructure in order to facilitate the collecting, storage, and processing of data of a high quality. Establishing electronic medical records that are standardised is absolutely necessary in order to guarantee that AI models have access to datasets that are comprehensive and trustworthy. In urban healthcare systems, it is possible to initiate pilot projects that combine artificial intelligence with pre-existing workflows in MRI and

laboratories. Once the efficacy and viability of the program has been proved, it may then be gradually scaled up to city-wide applications. In order to construct artificial intelligence models that are context-specific, culturally sensitive, and flexible to the resource fluctuation of urban India, it is vital for technology developers, physicians, and public health authorities to work together.

In addition, the development of patient-facing artificial intelligence apps for teaching and self-monitoring should be at the forefront of future developments. Reminders for chelation therapy may be provided via mobile applications, transfusion schedules could be monitored, and patients could be notified about follow-up requirements based on predictions produced by artificial intelligence. It would be possible for patients and carers to take an active part in the management of their condition if such tools were available. In addition, the incorporation of an artificial intelligence-driven population analytics system into city-level health initiatives has the potential to enhance long-term monitoring, policy planning, and the early detection of developing trends.

In light of this, artificial intelligence has enormous prospects to revolutionise the management of thalassaemia by improving diagnostic precision, making it possible to take preventative measures, and maximising the utilisation of healthcare resources. Using a roadmap that has been meticulously designed, urban healthcare systems in India have the potential to use these technologies in order to enhance patient outcomes, alleviate economic strain, and establish a precedent for the incorporation of artificial intelligence in the management of chronic diseases.

CONCLUSION

The results of this study have offered a complete knowledge of the role that artificial intelligence plays in improving predictive healthcare for the treatment of thalassaemia, with a particular emphasis on non-invasive options for diagnosing iron overload. It was emphasised in the review that iron overload had remained a critical complication in patients who were dependent on transfusions, and that the existing diagnostic landscape, despite being equipped with methods such as MRI T2* and serum ferritin testing, had faced limitations in terms of accessibility, accuracy, and cost. The review was a synthesis of insights from both global and Indian contexts. The research highlighted, across all of the theme divisions, how AI-driven models have emerged as transformational tools that were capable of bridging gaps in detection, monitoring, and management.

Based on the findings of the investigation, it was determined that non-invasive procedures driven by artificial intelligence had the potential to greatly alter predictive healthcare for patients with Thalassaemia. In the case of magnetic resonance imaging (MRI) images, the use of deep learning models has showed the capability to precisely quantify iron buildup and identify early organ involvement. Early risk stratification in urban settings with limited resources might be accomplished via the use of machine learning models that make use of biomarkers and clinical history. These models offered cost-effective solutions. These AI-enabled techniques have not only improved clinical accuracy but also decreased reliance on specialised expertise, which made it possible to treat high-risk patients in a more expedient and effective manner. This was accomplished by automating diagnostic processes. Due to the fact that early identification and appropriate management might prevent the development to permanent organ damage, the potential influence on lowering morbidity and death was clear.

In addition, the study highlighted the significant role that secondary data plays in the process of formulating evidence-based policy and of directing future research. Because of the availability of large datasets derived from public health reports, image archives, and hospital records, artificial intelligence models were able to be trained and verified without the requirement for substantial primary data collecting. Identifying patterns, risk factors, and gaps in the present healthcare ecosystem have shown to be quite beneficial through the use of secondary data analysis. Both academics and policymakers had developed the capacity to plan treatments, efficiently allocate resources, and develop methods for scaling AI-assisted solutions in urban healthcare contexts as a result of their reliance on these statistics.

Following the findings, unambiguous suggestions were made for the various parties. For the purpose of enhancing early detection, streamlining patient monitoring, and improving clinical decision making, it was advised that healthcare providers embrace diagnostic technologies that are supported by artificial intelligence (AI). The use of artificial intelligence into pre-existing non-invasive diagnostic applications, such as MRI-based iron measurement and biomarker evaluation, has the potential to facilitate proactive treatment while causing minimum disturbance to existing workflows. According to the findings of the study, governments should prioritise the development of comprehensive policies, the improvement of digital and medical infrastructure, and the establishment of ethical norms to regulate the deployment of artificial intelligence and data privacy in healthcare settings. It would be beneficial to build the framework for large-scale deployment by providing support for projects such as electronic medical records, secure data platforms, and pilot programs for artificial intelligence in public

institutions. According to the findings of the study, researchers should continue to investigate integrated artificial intelligence solutions that make use of a wide variety of secondary datasets. This will help improve accuracy, minimise bias, and guarantee that models are suited to the demographic and clinical reality of urban Indian populations.

According to the findings of the study, artificial intelligence-driven non-invasive healthcare solutions have the potential to revolutionise the management of Thalassaemia, lessen the burden of iron overload, and maximise the utilisation of urban healthcare resources. The route towards a healthcare model for Thalassaemia that is sustainable, predictive, and patient-centered has been attainable via the combination of the acceptance of technology, the support of policy, and research that is based on evidence.

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