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ARTIFICIAL INTELLIGENCE APPLICATIONS IN BLOOD BANKS: PROCESS OPTIMIZATION, DEMAND PREDICTION AND IMPROVEMENT IN HEALTHCARE MANAGEMENT

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ABSTRACT

Blood banks play a vital role in healthcare systems by ensuring the supply of safe, high-quality blood products. However, their management faces logistical challenges that impact operational efficiency and healthcare. Artificial intelligence is emerging as a strategic tool to optimise processes, anticipate demand and strengthen decision-making. However, its application in blood banks remains fragmented, with disparate studies and varied methodological approaches. This study aimed to identify the applications, benefits and challenges of using artificial intelligence in the management of blood banks, as well as technological developments in this area. To achieve this objective, a systematic review was conducted in accordance with the PRISMA 2020 guidelines, enabling the structured analysis of existing knowledge. The conclusions highlight the need to consolidate disciplined development and integrate technological advances with robust ethical frameworks, guiding future applications towards an efficient, inclusive and sustainable health ecosystem.

KEYWORDS: Artificial Intelligence; Blood Banks; Process Optimisation; Demand Forecasting; Healthcare Management.

1. INTRODUCTION

Blood banks are an essential component of healthcare systems. They collect, process, store and distribute the blood components necessary for various medical procedures. Properly functioning blood banks ensure the timely supply of safe, quality blood, which is essential for surgical interventions, cancer treatments, transplants and the care of patients with chronic diseases or traumatic emergencies (Niakan et al., 2024). The efficiency of blood banks affects both individual health and the overall performance of healthcare systems. Managing a blood bank presents significant logistical challenges. Blood components have a limited shelf life, so strict storage and rotation processes are required. Additionally, demand fluctuates due to seasonal factors, unforeseen emergencies, and demographic changes (Kwon et al., 2024).

These conditions increase the risk of shortages or, conversely, wastage due to expiry, affecting operational sustainability and compromising the timely delivery of healthcare (Farrington, 2025). Artificial intelligence (AI) is a vital tool for optimising blood bank management. Its capabilities enable it to streamline processes, predict demand, and support decision-making. These applications facilitate the anticipation of needs, reduce losses and enhance service efficiency (Singh et al., 2025). The importance of AI has increased in post-pandemic contexts where limited health resources and an ageing population require agile, precise solutions. Despite recent advances in the application of this technology in healthcare, the use of artificial intelligence in blood banks remains a dispersed and poorly systematised field (Talukdar & Bhattacharya, 2025).

Current initiatives tend to focus on demand forecasting, inventory optimisation, or improving logistics processes. However, these efforts are fragmented, preventing the consolidation of a coherent body of knowledge on the scope, limitations and outcomes achieved in various contexts (Waheeb, 2024). This fragmentation is evident in the form of isolated studies, heterogeneous methodological approaches, and disparate technological applications, with no articulation to allow the identification of common patterns or generalisable learning (Al-Riyami et al., 2025). This dispersion has also limited the systematic approach to the technical, ethical and regulatory challenges that accompany the implementation of artificial intelligence in blood banks (Elhaj et al., 2024). This lack of integration hinders the development of a broad perspective to guide future applications and projects.

A comprehensive vision is necessary in order to strengthen the design of strategies, formulate effective policies, and create technological solutions that are aligned with the real needs of health systems. The objective of this research is therefore to identify the applications, benefits, challenges and technological developments associated with the use of artificial intelligence in blood banks, with the aim of optimising health management. To achieve this, a series of guiding questions have been developed to structure the analysis in a clear and precise way.

1. Which artificial intelligence applications have been implemented most frequently in blood banks?
2. Which AI techniques have been used to predict demand for, or the availability or expiration of, blood components?
3. What benefits have been reported in terms of operational efficiency, waste reduction and quality of service as a result of using AI in blood banks?
4. What technical, ethical or regulatory challenges have arisen from the implementation of AI in blood management systems?
5. Which models or technological platforms have been developed to support blood banks in making decisions using AI?

Although there are studies on the specific applications of artificial intelligence in blood banks, comprehensive reviews consolidating the available knowledge are still lacking. This research adds value by offering a systematic synthesis of existing applications, identifying gaps in the development and implementation of these technologies, and providing clear guidance on future applications, management policies, and areas of research in the healthcare field.

2. METHODOLOGY

A systematic review is a rigorous methodological tool that organises, synthesises and analyses the available knowledge on a specific topic in a structured way. This allows gaps, trends and challenges to be identified to support new research. This study adopted the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which are recognised as an international benchmark for the preparation and presentation of systematic reviews (Page et al., 2021). These guidelines provide a detailed framework that ensures transparency, completeness and reproducibility in the search, selection and analysis of scientific information. Additionally, the PRISMA flowchart was employed to document each phase of the study selection process, from initial identification to final inclusion, ensuring traceability and facilitating understanding of the applied procedure.

2.1. Eligibility Criteria

The selection of studies was made based on inclusion criteria designed to ensure the relevance and quality of the analysed documents. Articles published in Spanish or English were included as these are the languages with the greatest international scientific output in artificial intelligence and health. This restriction was consistent with the available resources for analysis and facilitated understanding of the content. The temporal criterion was set at the last ten years, a period during which the use of artificial intelligence in healthcare has shown significant development. This timeframe was chosen to identify recent studies reflecting technological advances in blood bank management.

The types of documents included were original research articles and reviews, as these allowed empirical results and synthesised knowledge to be obtained to strengthen the comprehensive analysis of the topic. There was also a requirement for a direct relationship between the content of the study and the use of artificial intelligence in blood banks, as reflected in its objectives, methodology or results. The process involved three phases of exclusion. The first phase involved removing duplicate records or documents with incorrect metadata. The second phase involved discarding studies for which the full text could not be obtained due to access restrictions or editorial unavailability. The third phase involved exclusion based on thematic criteria, through reviewing titles, abstracts, and full texts to eliminate studies that, although mentioning artificial intelligence or blood banks, did not address their interrelationship or provide useful evidence for this research.

2.2. Sources of Information

The search for information was carried out using two robust and comprehensive databases. Scopus and Web of Science were chosen because they offer access to reliable, up-to-date international scientific literature on health, technology, and artificial intelligence. Scopus was chosen for its multidisciplinary approach and strength in science, technology and medicine. This database indexes peer-reviewed articles and conference proceedings, enabling the integration of studies from various disciplines that are necessary for addressing cross-cutting issues, such as the use of artificial intelligence in blood banks. Its coverage of emerging literature provides access to recent studies that are unavailable on other platforms (Asubiaro et al., 2024).

Web of Science was used due to its status as a leading source of validated scientific literature. This database operates with strict indexing criteria, guaranteeing high-quality standards in the documents consulted. Its structure enables bibliometric analyses to be conducted that reinforce control and traceability of searches (Asubiaro et al., 2024). Combining Scopus and Web of Science expanded thematic and disciplinary coverage, reducing the risk of bias associated with limitations from a single source and ensuring an exhaustive search to obtain a comprehensive view of the use of artificial intelligence in blood bank management.

2.3. Search Strategy

A specific equation was created for each database as part of the search strategy. This definition corresponded to the established inclusion criteria. In Scopus, the following equation was applied: TITLE-ABS-KEY ('artificial intelligence' OR 'machine learning') AND (TITLE ('blood bank' OR 'blood supply' OR 'blood donation') OR KEY ('blood bank' OR 'blood supply' OR 'blood donation'). This structure incorporated Boolean operators and key terms relating to artificial intelligence and blood banks.

In Web of Science, the following was used: TS=("artificial intelligence" OR "machine learning") AND (TS=("blood bank" OR "blood supply" OR "blood donation") OR AK=("blood bank" OR "blood supply" OR "blood donation")). The technical adaptation ensured correspondence with the interface of each platform. Initial validation verified the thematic relevance of the retrieved records with respect to the inclusion criteria.

2.4. Selection Process

The selection process was carried out in a structured sequence. First, the logs were downloaded from each database. Duplicates and entries with incorrect metadata were then removed. The titles and abstracts were reviewed to exclude studies that were not directly related to artificial intelligence in blood banks. This was followed by a thorough reading of the pre-selected texts. The final selection was made by consensus among the researchers to ensure thematic relevance. This procedure enabled 31 documents to be identified that met the defined inclusion criteria.

Figure 1 shows the corresponding flow chart for the study selection process, in line with the PRISMA 2020 guidelines. This scheme documents each stage of the procedure, from the initial identification of records to the final inclusion of the analysed studies.

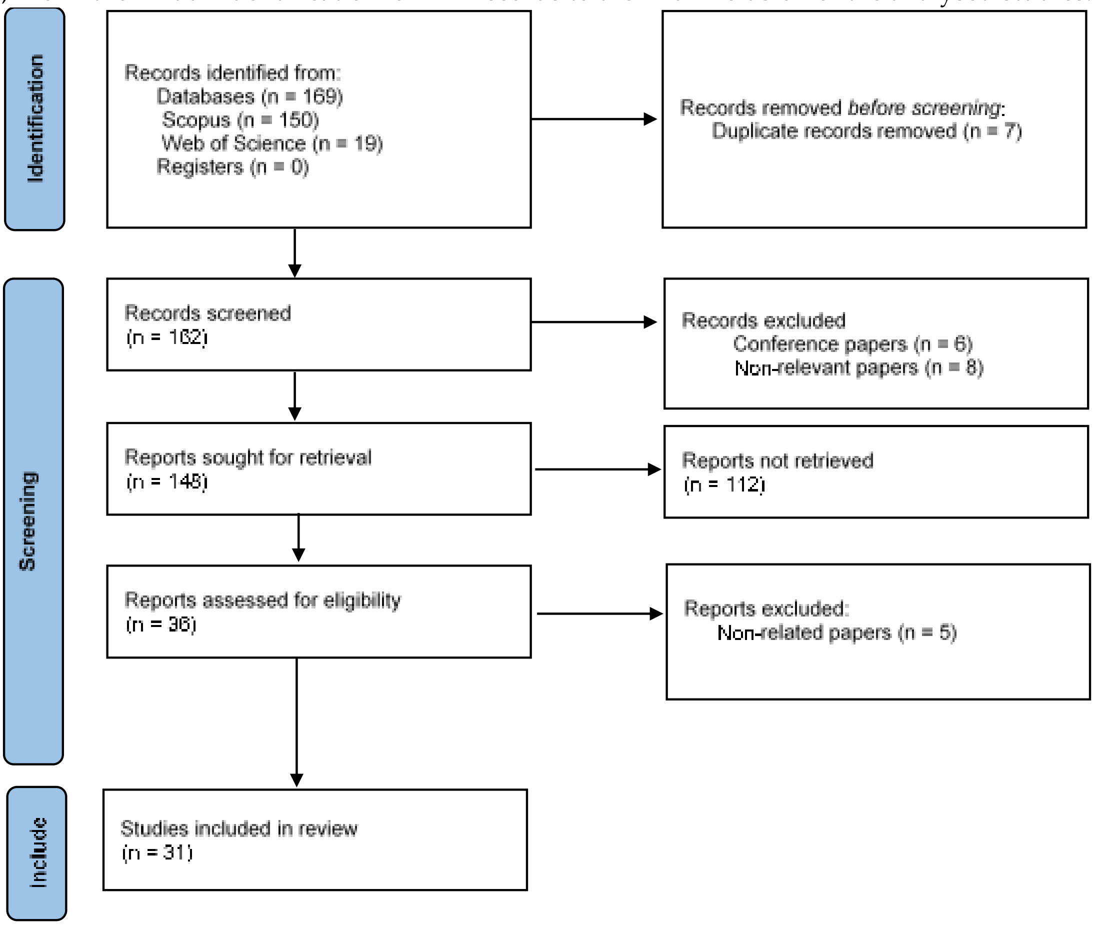

Figure 1: PRISMA Flowchart. Created Using Data From Scopus And Web Of Science.

2.5. Data Processing

Data processing was carried out using Microsoft Excel as a classification and systematisation tool. Matrices were constructed using variables such as year of publication, study type, applications, benefits and challenges. This structure facilitated the organisation and analysis of the findings. Cross-checking between investigators verified the correct assignment of categories and minimised the risk of omissions or errors.

2.6. Risk of Bias

The risk of bias in this review relates to the restriction to studies in Spanish and English, which limited the inclusion of contributions in other languages. Limitations are also recognised due to access being restricted to commercial databases, which could result in the exclusion of studies not indexed in Scopus or Web of Science. The design of the search equations was subject to bias due to term selection. Additionally, there is a risk of reporting bias due to the tendency to report positive results. Applying the PRISMA 2020 flow, as presented in Figure 1, helped to mitigate these limitations.

3. RESULTS

The results are organised according to the research questions. This structure enables the analysis to be organised and facilitates the identification of patterns, thematic gaps and particularities in the reviewed studies. Organising by analytical axes provides a comprehensive overview of the applications, benefits, challenges and technological developments associated with the use of artificial intelligence in blood banks. Table 1 is included to support the detailed analysis and summarises the selected studies.

Table 1: Studies Included In the Research. Based On Scopus And Web Of Science.

Title	**Authors**

Artificial intelligence-assisted diagnosis of early allograft dysfunction based on ultrasound image and data	Meng et al. (2025)
From Eye Movements to Personality Traits: A Machine Learning Approach in Blood Donation Advertising	Balaskas et al. (2024)
Multiple Explainable Approaches to Predict the Risk of Stroke Using Artificial Intelligence	Chadaga et al. (2023)
Smart Platform for Data Blood Bank Management: Forecasting Demand in Blood Supply Chain Using Machine Learning	Ben Elmir et al. (2023)
3D convolutional neural networks for stalled brain capillary detection	Solovyev et al. (2022)
A Drone-Based Blood Donation Approach Using an Ant Colony Optimization Algorithm	Abbas et al. (2023)
A Machine Learning Approach for Stroke Differential Diagnosis by Blood Biomarkers	Sherif & Ahmed (2024)
An Artificial-Intelligence-Based omnichannel blood supply chain: A pathway for sustainable development	Ghouri et al. (2023)
Barriers and enablers to and strategies for promoting domestic plasma donation throughout the world: Overarching protocol for three systematic reviews	Etherington et al. (2023)
CIsense: an automated framework for early screening of cerebral infarction using PPG sensor data	Gupta et al. (2024)
Comparative analysis of GPT-3.5 and GPT-4.0 in Taiwan's medical technologist certification: A study in artificial intelligence advancements	Yang et al. (2024)
Comparison of Time Series Methods and Machine Learning Algorithms for Forecasting Taiwan Blood Services Foundation's Blood Supply	Shih & Rajendran (2019)
Computer-Based Blood Type Identification Using Image Processing and Machine Learning Algorithm	Rosales & de Luna (2022)
Corpus Callosum Atrophy in Detection of Mild and Moderate Alzheimer's Disease Using Brain Magnetic Resonance Image Processing and Machine Learning Techniques	Das et al. (2021)
Demand forecasting for platelet usage: From univariate time series to multivariable models	Motamedi et al. (2024)
Development of a quantitative prediction algorithm for human cord blood-derived CD34+ hematopoietic stem-progenitor cells using parametric and non-parametric machine learning models	Leung et al. (2024)
Dynamic cerebral blood flow assessment based on electromagnetic coupling sensing and image feature analysis	Gong et al. (2024)
Explainable haemoglobin deferral predictions using machine learning models: Interpretation and consequences for the blood supply	Vinkenoog et al. (2022)
FSR-Based Smart System for Detection of Wheelchair Sitting Postures Using Machine Learning Algorithms and Techniques	Jaffery et al. (2022)
Generative AI-Powered Synthetic Data for Enhancing Predictive Analytics in Blood Donation Supply Management: A Comparative Study of Machine Learning Models	Hong et al. (2025)
Genetic Folding (GF) Algorithm with Minimal Kernel Operators to Predict Stroke Patients	Mezher, M. A. (2022)
Machine learning algorithms for forecasting and backcasting blood demand data with missing values and outliers: A study of Tema General Hospital of Ghana	Twumasi & Twumasi (2022)
Machine learning-based prediction of fainting during blood donations using donor properties and weather data as features	Suessner et al. (2022)
Objective assessment of stored blood quality by deep learning	Doan et al. (2020)
Phage Immunoprecipitation-Sequencing Reveals CDHR5 Autoantibodies in Select Patients With Interstitial Lung Disease	Upadhyay et al. (2024)
Predicting haemoglobin deferral using machine learning models: Can we use the same prediction model across countries?	Meulenbeld et al. (2024)
Predicting the intention to donate blood among blood donors using a decision tree algorithm	Salazar et al., (2021)
Prediction of blood supply in vestibular schwannomas using radiomics machine learning classifiers	Song et al. (2021)
Pulse wave-based evaluation of the blood-supply capability of patients with heart failure via machine learning	Wang et al. (2024)
Relationship between Circle of Willis Variations and Cerebral or Cervical Arteries Stenosis Investigated by Computer Tomography Angiography and Multitask Convolutional Neural Network	Hou et al. (2021)
Stroke Risk Prediction with Machine Learning Techniques	Dritsas & Trigka (2022)

Figure 2 illustrates the distribution of AI application types collected in the systematic review. The most common category is demand forecasting, followed by risk forecasting. Other notable categories include the analysis of donor behaviour and applications in medical imaging and cardiovascular evaluation. Applications were also identified in disease diagnosis, behaviour prediction, and supply chain optimisation. This classification provides an overview of the applications of artificial intelligence in blood banks.

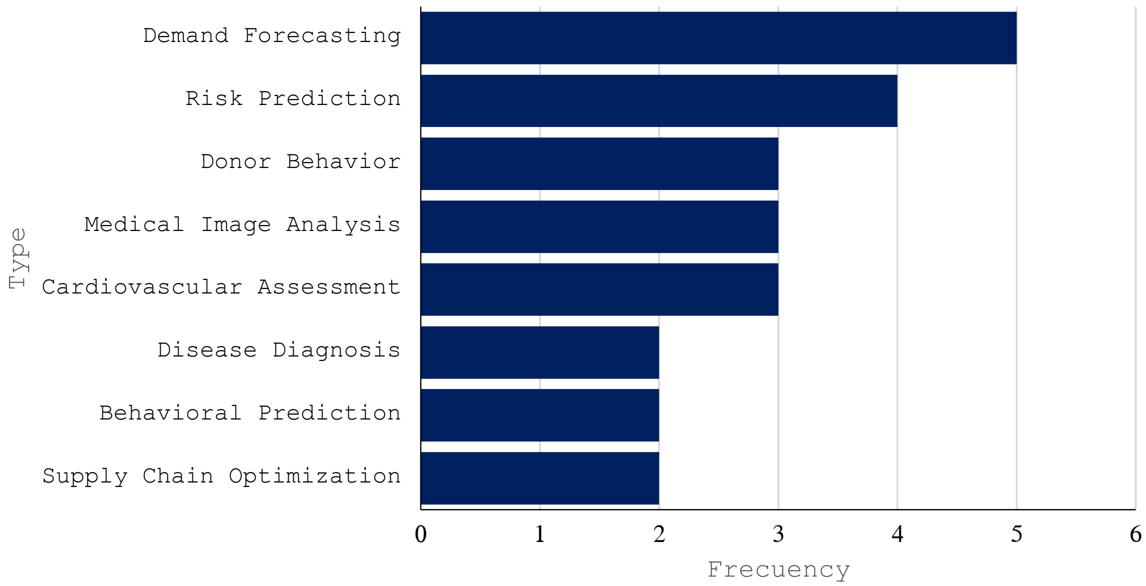

Figure 2: Types Of Applications Identified. Created By The Author Using Data From Scopus And Web Of Science.

Figure 3 illustrates the distribution of artificial intelligence techniques identified in the reviewed studies. The most commonly used techniques are deep learning, convolutional neural networks, support vector machines, decision trees and random forests. Other techniques recorded include optimisation algorithms, generative learning, time series models, explainability techniques and dimensionality reduction methods. This classification enables us to observe the variety of approaches to the application of artificial intelligence in blood bank management.

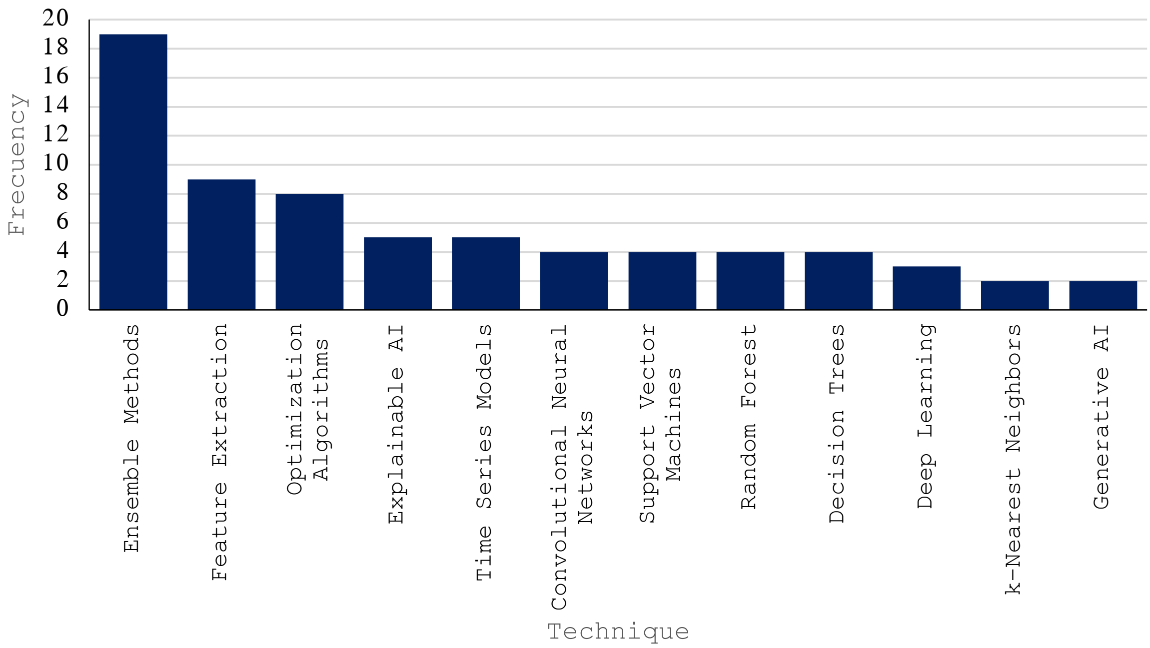

Figure 3: AI Techniques Identified. Created By The Author Using Data From Scopus And Web Of Science.

Figure 4 shows the distribution of concrete benefits reported in the reviewed research. Improvements in accuracy and predictive performance are particularly notable. Contributions to model robustness, interpretability, and the accuracy of forecasts are also evident. Other benefits include the identification of risk factors, the efficient allocation of resources, time reduction, support for clinical decision-making, and strategies to strengthen donor commitment. This classification highlights the most common benefits associated with the use of artificial intelligence in blood banks.

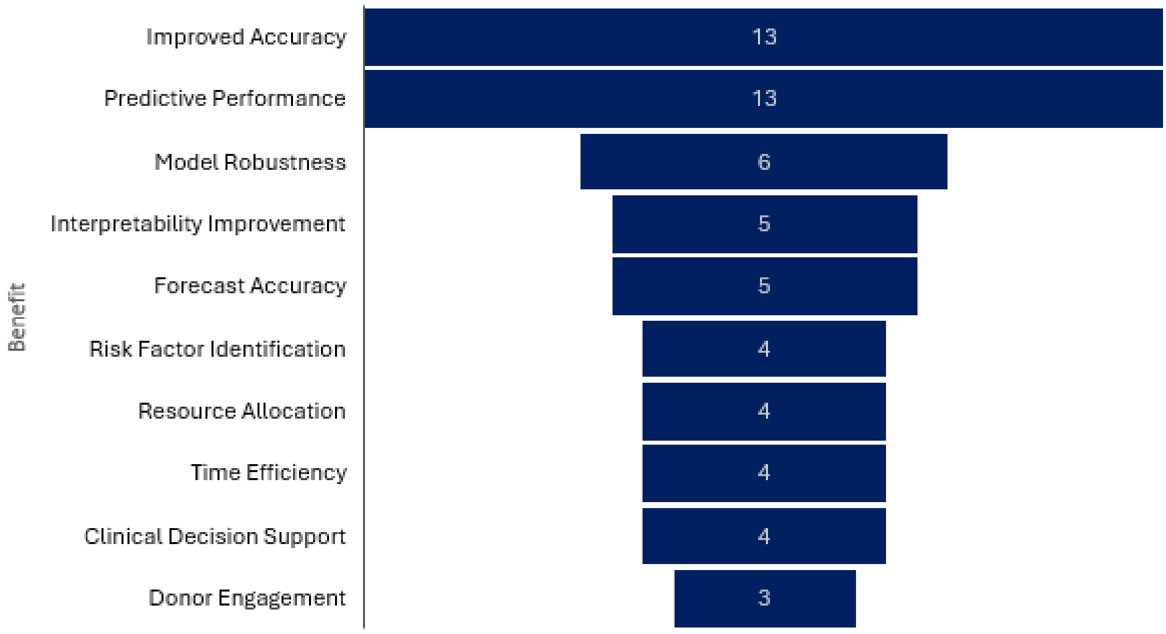

Figure 4: Concrete Benefits Identified. Created By The Author Using Data From Scopus And Web Of Science.

Figure 5 shows how the challenges identified in the analysed research on the application of artificial intelligence to blood banks are distributed. The main limitations are data availability and quality, followed by difficulties in model interpretation, technical complexity and computational demands. Ethical challenges, privacy risks, cost constraints, infrastructure limitations and regulatory barriers were also identified. This classification enables us to identify the areas that require attention in order to advance the development and implementation of these applications.

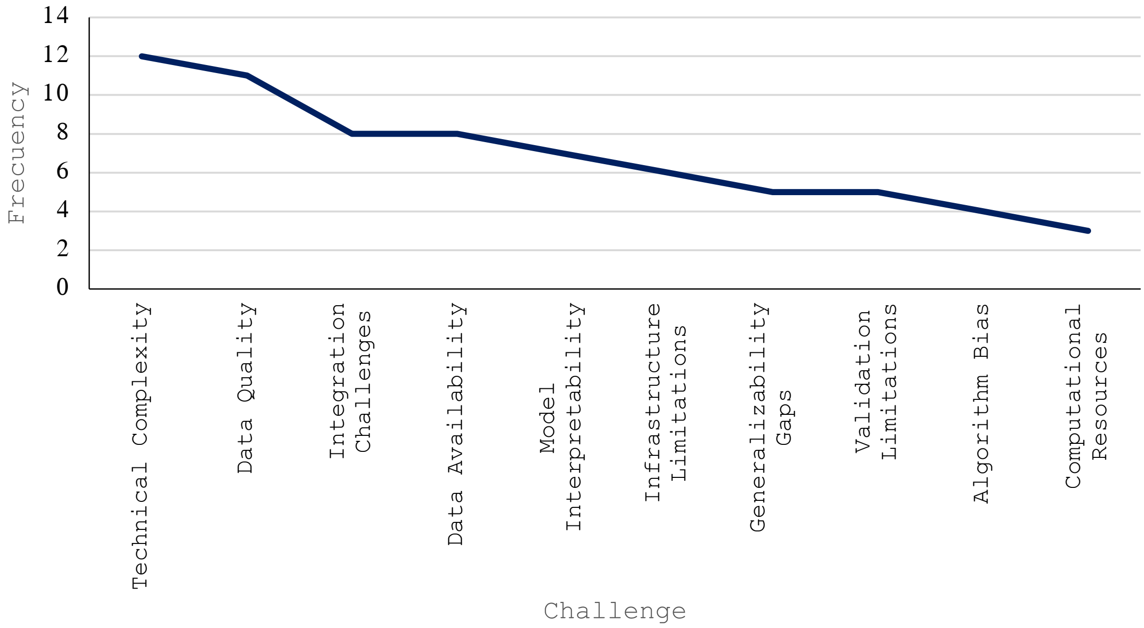

Figure 5: Challenges Identified In Studies. Own Elaboration Based On Scopus And Web Of Science.

Figure 6 shows a variety of models and platforms used for artificial intelligence applications in blood banks. The results include Python-, R-, and MATLAB-based platforms, as well as LabVIEW interfaces and WEKA and Docker tools. Cloud infrastructures, pre-trained deep learning frameworks and omics data integration tools are also identified. This diversity demonstrates the wide range of technological approaches employed in developing these applications.

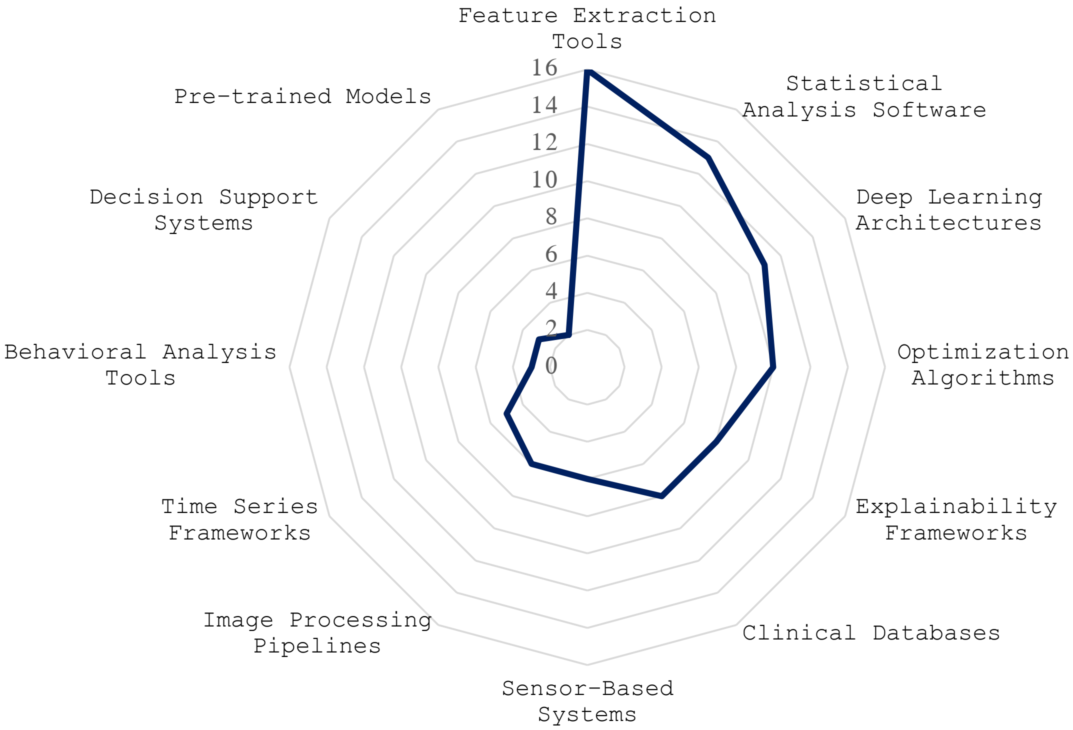

Figure 6: Specific Models and Platforms. Original Work Based On Scopus and Web Of Science.

The results were organised according to the research questions, enabling the information to be structured clearly and coherently. This organisation made it easier to identify patterns, common approaches and thematic gaps in the use of artificial intelligence in blood banks. The overall classification provides an integrated view of applications, techniques, benefits, challenges and documented models. This approach provides an understanding of the current state of the field and establishes a foundation for guiding future research.

4. DISCUSSION

The discussion is organised around an analysis of the results in relation to the objectives and research questions. First, the main findings are presented, and then they are compared with previous studies on artificial intelligence in blood banks. Next, a conceptual framework based on the analysis is proposed. Finally, the theoretical, political and practical implications are discussed, the limitations of the study are highlighted and future research areas aimed at advancing the field are suggested.

4.1. Analysis of Results

The results show that the main aim of using artificial intelligence in blood banks is to improve critical processes such as demand and risk prediction in order to respond to challenges such as shortages and wastage of units (Shih & Rajendran, 2019). These applications optimise inventory and logistics decisions and have led to the development of intelligent platforms combining techniques such as deep learning and optimisation algorithms to reduce management uncertainty (Ben Elmir et al., 2023). This trend also encompasses the use of image processing via decision trees for the automatic identification of blood groups, thereby enhancing accuracy and mitigating risks in care (Rosales & de Luna, 2022).

Similarly, diagnostic models such as genetic algorithms applied to stroke prediction expand the scope towards the prevention and treatment of circulatory diseases (Mezher, 2022). Conversely, explainable techniques in automated diagnoses, as demonstrated in cases of postpartum depression (Shivaprasad et al., 2024), bolster clinical confidence in these models. Meanwhile, technologies such as three-dimensional neural networks offer operational advantages in complex tasks, such as pattern detection in biomedical images (Solovyev et al., 2022). This diversity of applications reflects the potential of artificial intelligence to address multiple clinical and operational needs and improve the accuracy and predictive performance of decision-making processes.

However, the results also highlight significant challenges in implementing these technologies. These include the quality of available data, technical barriers and infrastructure limitations. These factors affect both the accuracy of the models and their operational viability (Abbas et al., 2023). Added to this are structural obstacles such as the absence of adequate regulatory frameworks and institutional mistrust, which are particularly evident in contexts in the Global South (Borines et al., 2025). This highlights the need to strengthen technical capacities, establish clear standards and define effective adoption strategies.

Finally, the diversity of models and platforms used highlights the convergence between traditional tools and advanced technological environments. This variety enables responses to different technical requirements and facilitates the integration of complex processes, such as behavioural analysis through eye tracking combined with machine learning algorithms (Balaskas et al., 2024). Similarly, adopting specialised frameworks and technological adaptations aligns with trends observed in other sectors, where choosing the right platforms directly influences operational efficiency (Wang et al., 2023).

4.2. Comparison of Results With Other Studies

The results of this research show both similarities and differences with previous studies on the application of artificial intelligence to health management, particularly in the context of blood banks. Classifying the types of applications and techniques used, as well as the reported benefits and challenges encountered, enables these findings to be positioned within the broader context of artificial intelligence use in healthcare. One notable similarity is the use of artificial intelligence to enhance clinical and operational decision-making, as emphasised by Almadani et al. (2025) in their review of distributed decision support systems (DDSS) in healthcare. The authors demonstrate that technologies such as artificial intelligence and the Internet of Medical Things (IoMT) optimise processes such as diagnosis and treatment. This is consistent with the benefits identified in this review for blood banks, where artificial intelligence enhances diagnostic accuracy and predictive performance.

However, while Almadani et al. (2025) examine distributed decision-making systems in general clinical settings, the present research focuses on applications for blood banks. This thematic difference underscores the specificity of the study and its contribution to specialised knowledge in the field of transfusion. Regarding demand prediction, the results are consistent with those of Liu et al. (2025), who used a Transformer model to estimate platelet demand through apheresis. Both studies demonstrate that predictive models optimise inventory management and reduce waste. However, while Liu et al. (2025) conducted a quantitative analysis focused on a single blood component (platelets), the current review offers a more comprehensive view, ranging from demand prediction to diagnosis and clinical assessment. This broadens the thematic scope of the study.

In terms of stochastic approaches and optimisation techniques in donation management, there is a degree of overlap with the model of Elyasi et al. (2025), who use stochastic programming and donor segmentation to enhance supply efficiency. However, the present study differs in that it systematically identifies a variety of methodological approaches reported by other authors, whereas Elyasi et al. (2025) develop a specific technical proposal. The complementarity of the two approaches highlights the diversity of methods and the need for integrated solutions. Similarities can also be found in the work of Orhan and Kurutkan (2025), who use machine learning to predict demand for health services by integrating predisposing and contextual factors.

This coincidence confirms the relevance of predictive approaches based on artificial intelligence in various healthcare management scenarios. While Orhan and Kurutkan (2025) consider the demand within the healthcare system as a whole, the present study restricts its analysis to the transfusion setting. The challenges identified in this review are related to the limitations described by Cao et al. (2025) in clinical biochemistry, particularly with regard to ethical considerations, algorithmic biases and costs. These obstacles coincide with those documented in artificial intelligence applications in blood banks, confirming the transversality of these challenges in the healthcare sector. This study builds on previous work by providing a structured classification and specific thematic analysis of artificial intelligence in blood banks, setting a standard for future research.

4.3. Conceptual Framework Proposal

Figure 7 shows the conceptual framework derived from the results. The scheme integrates the following:

type of application; artificial intelligence technique; model or platform; and concrete benefits and challenges. This structure enables you to visualise the relationships and dependencies. Challenges can limit the achievement of benefits. The model will guide future research towards the most effective combinations of techniques, applications and platforms. It also suggests ways to overcome critical barriers and promote the efficient use of artificial intelligence in blood banks.

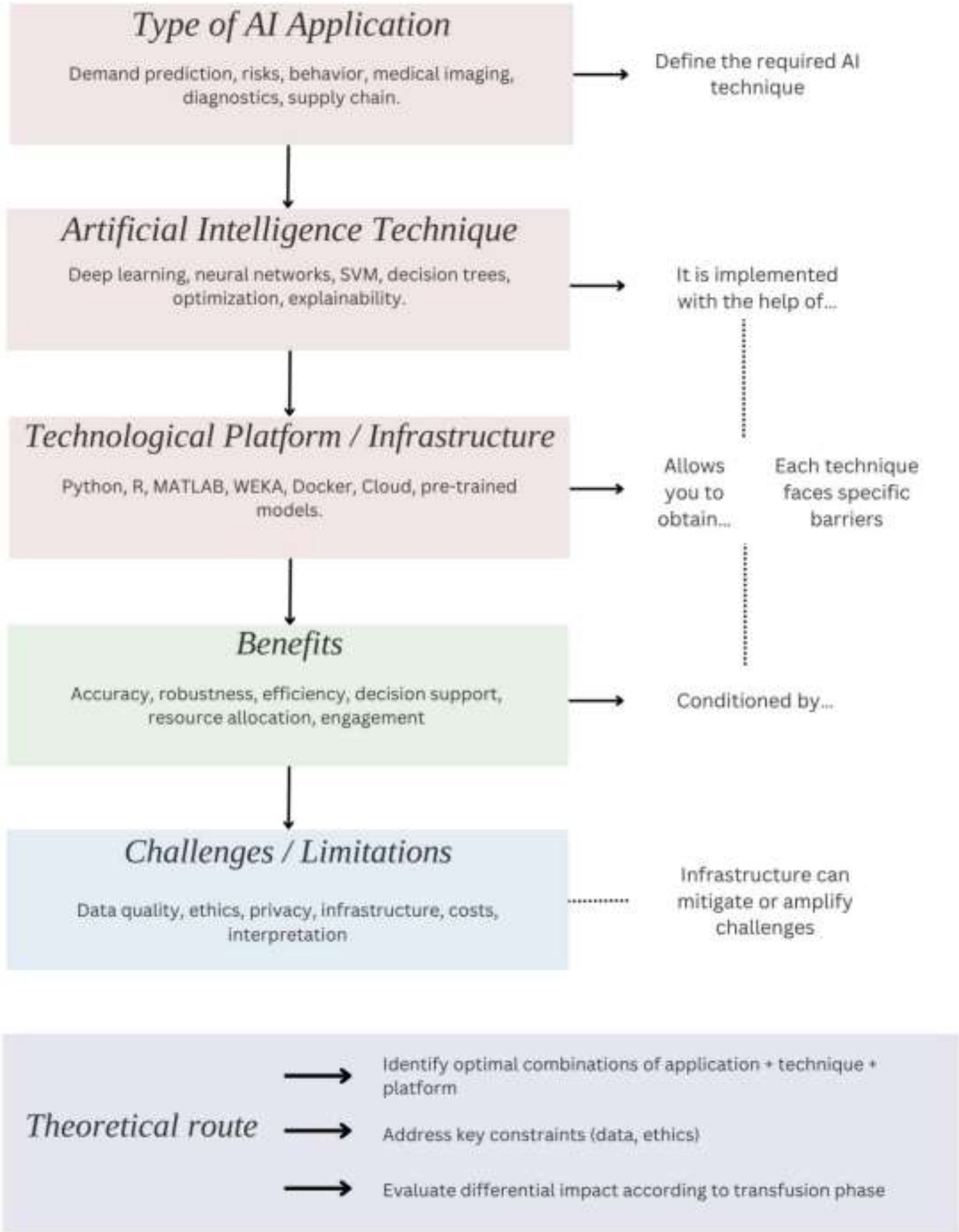

Figure 7. Proposed Conceptual Framework. Own Elaboration.

4.4. Implications

This research on artificial intelligence applications in blood banks has generated theoretical, political and institutional implications, as well as practical recommendations for healthcare professionals. At a theoretical level, the findings reinforce our understanding of the relationship between artificial intelligence and health management, particularly in the context of blood banks, an area in which research is still limited. The structured classification of applications, techniques, models, benefits and challenges provides a systematic basis for consolidating conceptual frameworks and improving our understanding of how these technologies function in clinical settings. The analysis shows that artificial intelligence techniques require specific methodological configurations depending on the application type and platform. This relationship suggests a clear theoretical approach: identifying optimal combinations of applications, techniques, and computational environments to generate better results in terms of accuracy, efficiency, and security.

Recognising recurring challenges, such as limitations in data quality, infrastructural barriers and ethical restrictions, enriches theoretical approaches to the development of artificial intelligence systems in healthcare. These approaches incorporate contextual and structural variables absent from generalist technological proposals. At the political and institutional level, the results highlight the importance of establishing regulatory frameworks that promote the responsible adoption of artificial intelligence in blood banks. Policies are needed to ensure transparency, security, and accessibility in the face of challenges related to data privacy, algorithmic biases, interoperability, and costs. Priority must be given to strengthening regulatory frameworks with ethical and technical standards for the treatment of clinical data. Incentives must also be established to encourage health institutions to invest in adequate infrastructure and the training of personnel specialising in the use of advanced technologies. The findings also demonstrate the importance of promoting collaboration between the public, private, and academic sectors.

Transferring knowledge from universities and research centres to hospitals, blood banks and health organisations must become a priority. Advancing policies for standardising platforms and computer languages that allow interoperability between systems is essential for integrating artificial intelligence into everyday clinical processes. From a practical standpoint, the results allow concrete recommendations to be made to different stakeholders. Institutions responsible for transfusion management must invest in improving data quality and developing robust electronic registration systems that provide predictive models with reliable information. It is also recommended that interdisciplinary teams be formed, integrating health professionals, artificial intelligence specialists, data engineers and ethical leaders. This integration ensures that the design, implementation and evaluation of systems respond to scientific, technical and social criteria.

A key recommendation for researchers is to study optimal combinations of techniques, applications and platforms in depth, taking into account the particularities of each health context. Furthermore, research into model explainability and transparency must be expanded to bolster clinical users' confidence in decision support systems.

Another necessary step is to analyse the differential impact of the reported benefits in each phase of the transfusion process, from blood collection to distribution. The results show the importance of designing modular and scalable technological solutions adapted to different levels of infrastructure for developers of such solutions.

From the outset, it is recommended that algorithmic auditing and ethical data management mechanisms are incorporated. Intuitive interfaces for non-IT users must also be developed. Taking these actions ensures that developments are technically, operationally and institutionally efficient. The findings provide concrete evidence to strengthen the link between theory, policy and practice in the use of artificial intelligence in blood banks. This approach establishes a benchmark for structured progress in this field.

4.5. Limitations

This study has methodological, theoretical and empirical limitations that must be acknowledged. In terms of methodology, although rigorous selection criteria were applied, the review was limited to Scopus and Web of Science. This may have excluded relevant literature from other repositories or grey sources. Thematic classification depended on interpretative analysis, which introduces subjectivity, despite efforts to maintain consistency. In terms of the theoretical approach, while the research describes and categorises applications, benefits, challenges and platforms, it does not develop explanatory frameworks that integrate causal relationships between these elements.

This limits the potential to generate hypotheses that can be transferred to other contexts. Empirically, the study is based on the results of previous research and does not incorporate case studies or direct operational validation. This reduces the ability to practically test combinations of applications, techniques, and platforms. Overcoming these limitations will require future studies to adopt a mixed approach, develop stronger theoretical frameworks and conduct empirical validations in real blood banks.

4.6. Lines of Future Research

The projections for future research derived from this study enable us to identify specific areas that address the identified implications and limitations. One priority should be to develop empirical studies that validate the most effective combinations of application type, artificial intelligence technique and technological platform. This approach involves direct testing in real blood banks to fill practical gaps. These studies will determine which configurations offer the best results in terms of accuracy, operational efficiency and clinical safety when adjusted to different institutional contexts. Another relevant area of research is the development of explanatory theoretical frameworks that model the causal relationships between applications, techniques, benefits and challenges. This will enable comparable hypotheses to be structured between different health institutions.

To strengthen their applicability, these frameworks must incorporate contextual variables such as technological infrastructure, institutional capacities and the regulatory environment. Studies that identify and propose solutions to the most common challenges detected in the review are also necessary. Priorities include data quality, interoperability, costs and ethics. Research should focus on data management and governance methodologies that guarantee integrity, privacy and traceability — key aspects for building trust in the use of artificial intelligence in healthcare. Additionally, studies analysing the differential impact of reported benefits in the various phases of the transfusion process must be advanced.

This will enable us to determine where the benefits are concentrated, e.g. in collection, processing or distribution, and guide the prioritisation of resources and interventions. Interdisciplinary research combining artificial intelligence, bioethics, public health and health management is recommended. This approach will facilitate integrated proposals that consider technical, social, ethical, and organisational aspects. This interdisciplinary approach will enable the design of robust and sustainable solutions that address the real challenges of transfusion management. These lines of research offer a structured and coherent approach to advancing the field.

5. CONCLUSIONS

This study's conclusions enable us to identify the emerging role of artificial intelligence in blood banks, which is a transforming field. The review confirms sustained growth in interest in applying these technologies to transfusion. This scenario presents both challenges and opportunities for the consolidation of structured development oriented towards the actual needs of the healthcare sector. The diversity of approaches demonstrates that there is no universal implementation model. In this context, artificial intelligence requires specific adaptations to each operational and institutional environment.

This situation enables us to strengthen the link between technological development, health management, and ethical responsibility. Future advancement in this field will depend not only on improving predictive capacity and efficiency, but also on building a robust ecosystem. This ecosystem must guarantee transparency, respect for patients' rights, and institutional sustainability. Addressing these challenges as an integral part of development will enable artificial intelligence in blood banks to establish itself as a key component of more robust, inclusive and efficient healthcare systems.

REFERENCES

Abbas, S., Ashraf, F., Jarad, F., Sardar, M. S., & Siddique, I. (2023). A Drone-Based Blood Donation Approach Using an Ant Colony Optimization Algorithm.

Almadani, B., Kaisar, H., Thoker, I. R., & Aliyu, F. (2025). A systematic survey of distributed decision support systems in healthcare. Systems, 13(3), 157.

Al-Riyami, A. Z., Gammon, R. R., Seheult, J., Arora, S., & Goel, R. (2025). Artificial intelligence and transfusion education, research and practice: The view from the ISBT Clinical Transfusion Working Party. *Vox Sanguinis*.

Asubiaro, T., Onaolapo, S., & Mills, D. (2024). Regional disparities in Web of Science and Scopus journal coverage. Scientometrics, 129(3), 1469-1491. https://doi.org/10.1007/s11192-024-04948-x

Balaskas, S., Koutroumani, M., Rigou, M., & Sirmakessis, S. (2024). From Eye Movements to Personality Traits: A Machine Learning Approach in Blood Donation Advertising. *AI*, *5*(2), 635-666.

Ben Elmir, W., Hemmak, A., & Senouci, B. (2023). Smart platform for data blood bank management: forecasting demand in blood supply chain using machine learning. *Information*, *14*(1), 31.

Borines, A., Teckle, P., & Turi, A. N. (2025). Exploring the Current AI Landscape in Global South Economies: A Systematic Literature Review and Research Agenda. Tech Transformation and AI Readiness: Pioneering Paths for the Global South, 1-30.

Cao, H., Oghenemaro, E. F., Latypova, A., Abosaoda, M. K., Zaman, G. S., & Devi, A. (2025). Advancing clinical biochemistry: addressing gaps and driving future innovations. Frontiers in Medicine, 12, 1521126.

Chadaga, K., Sampathila, N., Prabhu, S., & Chadaga, R. (2023). Multiple explainable approaches to predict the risk of stroke using artificial intelligence. *Information*, *14*(8), 435.

Das, S., Panigrahi, P., & Chakrabarti, S. (2021). Corpus callosum atrophy in detection of mild and moderate Alzheimer's disease using brain magnetic resonance image processing and machine learning techniques. *Journal of Alzheimer's Disease Reports*, *5*(1), 771-788.

Doan, M., Sebastian, J. A., Caicedo, J. C., Siegert, S., Roch, A., Turner, T. R., ... & Carpenter, A. E. (2020). Objective assessment of stored blood quality by deep learning. *Proceedings of the National Academy of Sciences*, *117*(35), 21381-21390.

Dritsas, E., & Trigka, M. (2022). Stroke risk prediction with machine learning techniques. *Sensors*, *22*(13), 4670.

Elhaj, S. A., Odeh, Y., Tbaishat, D., Rjoop, A., Mansour, A., & Odeh, M. (2024). Informing the State of Process Modeling and Automation of Blood Banking and Transfusion Services Through a Systematic Mapping Study. *Journal of Multidisciplinary Healthcare*, 473-489.

Elyasi, M., Özener, O. Ö., Yanıkoğlu, İ., Ekici, A., & Dolgui, A. (2025). A column generation-based approach for the adaptive stochastic blood donation tailoring problem. International Journal of Production Research, 63(2), 703-728.

Etherington, C., Palumbo, A., Holloway, K., Meyer, S., Labrecque, M., Rubini, K., ... & Presseau, J. (2023). Barriers and enablers to and strategies for promoting domestic plasma donation throughout the world: Overarching protocol for three systematic reviews. *Plos one*, *18*(12), e0296104.

Farrington, J. M. (2025). *Machine learning and GPU-accelerated computing applied to platelet inventory management in a hospital blood bank* (Doctoral dissertation, UCL (University College London)).

Ghouri, A. M., Khan, H. R., Mani, V., ul Haq, M. A., & de Sousa Jabbour, A. B. L. (2023). An Artificial-Intelligence-Based omnichannel blood supply chain: A pathway for sustainable development. *Journal of Business Research*, *164*, 113980.

Gong, Z., Zeng, L., Jiang, B., Zhu, R., Wang, J., Li, M., ... & Chen, Y. (2024). Dynamic cerebral blood flow assessment based on electromagnetic coupling sensing and image feature analysis. *Frontiers in Bioengineering and Biotechnology*, *12*, 1276795.

Gupta, S., Singh, A., & Sharma, A. (2024). CIsense: an automated framework for early screening of cerebral infarction using PPG sensor data. *Biomedical engineering letters*, *14*(2), 199-207.

Hong, K. C., Ling, T. C., Islam, S., Kolandaisamy, R. A., Shibghatullah, A. S., Nidzam, N. N. S., ... & Zaman, H. B. (2025). Generative AI-Powered Synthetic Data for Enhancing Predictive Analytics in Blood Donation Supply Management: A Comparative Study of Machine Learning Models. *International Journal on Advanced Science, Engineering and Information Technology*, *15*(1), 9-19.

Hou, J., Gao, M. Y., Pan, A. Z., Wang, Q. D., Liu, B., Jin, Y. B., ... & Wang, W. (2021). Relationship between circle of Willis variations and cerebral or cervical arteries stenosis investigated by computer tomography angiography and multitask convolutional neural network. *Journal of Healthcare Engineering*, *2021*(1), 6024352.

Jaffery, M. H., Ashraf, M. A., Almogren, A., Asim, H. M., Arshad, J., Khan, J., ... & Hussen, S. (2022). FSR-Based Smart System for Detection of Wheelchair Sitting Postures Using Machine Learning Algorithms and Techniques. *Journal of Sensors*, *2022*(1), 1901058.

Kwon, H. J., Park, S., Park, Y. H., Baik, S. M., & Park, D. J. (2024). Development of blood demand prediction model using artificial intelligence based on national public big data. *Digital Health*, *10*, 20552076231224245.

Leung, C. K., Zhu, P., Loke, I., Tang, K. F., Leung, H. C., & Yeung, C. F. (2024). Development of a quantitative prediction algorithm for human cord blood-derived CD34+ hematopoietic stem-progenitor cells using parametric and non-parametric machine learning models. *Scientific Reports*, *14*(1), 25085.

Liu, P., Mou, T., Luo, Y., Li, Y., Li, W., Kuang, Y. Q., & Duan, Y. Prediction of Apheresis Platelet Demand and Inventory Management Via the Transformer Model. Available at SSRN 5123902.

Meng, Y., Wang, M., Niu, N., Zhang, H., Yang, J., Zhang, G., ... & Wang, K. (2025). Artificial intelligence-assisted diagnosis of early allograft dysfunction based on ultrasound image and data. *Visual Computing for*

Industry, Biomedicine, and Art, *8*(1), 1-10.

Meulenbeld, A., Toivonen, J., Vinkenoog, M., Brits, T., Swanevelder, R., de Clippel, D., ... & Arvas, M. (2024). Predicting haemoglobin deferral using machine learning models: Can we use the same prediction model across countries?. *Vox Sanguinis*, *119*(7), 758-763.

Mezher, M. A. (2022). Genetic folding (GF) algorithm with minimal kernel operators to predict stroke patients. *Applied Artificial Intelligence*, *36*(1), 2151179.

Motamedi, M., Dawson, J., Li, N., Down, D. G., & Heddle, N. M. (2024). Demand forecasting for platelet usage: From univariate time series to multivariable models. *Plos one*, *19*(4), e0297391.

Niakan, P. B., Keramatpour, M., Afshar-Nadjafi, B., & Komijan, A. R. (2024). An Integrated Supply Chain Model for Predicting Demand and Supply and Optimizing Blood Distribution. *Logistics*, *8*(4), 134.

Orhan, F., & Kurutkan, M. N. (2025). Predicting total healthcare demand using machine learning: separate and combined analysis of predisposing, enabling, and need factors. BMC Health Services Research, 25(1), 366.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. bmj, 372. https://doi.org/10.1136/bmj.n71

Rosales, M. A., & de Luna, R. G. (2022). Computer-based blood type identification using image processing and machine learning algorithm. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *26*(5), 698-705.

Salazar-Concha, C., & Ramírez-Correa, P. (2021). Predicting the intention to donate blood among blood donors using a decision tree algorithm. *Symmetry*, *13*(8), 1460.

Sherif, F. F., & Ahmed, K. S. (2024). A machine learning approach for stroke differential diagnosis by blood biomarkers. *J. Adv. Inf. Technol*, *15*(1), 1-9.

Shih, H., & Rajendran, S. (2019). Comparison of time series methods and machine learning algorithms for forecasting Taiwan Blood Services Foundation's blood supply. *Journal of healthcare engineering*, *2019*(1), 6123745.

Shivaprasad, S., Chadaga, K., Sampathila, N., Prabhu, S., Chadaga P, R., & KS, S. (2024). Explainable machine learning methods to predict postpartum depression risk. Systems Science & Control Engineering, 12(1), 2427033.

Singh, T., Kathuria, M., & Sharma, S. (2025). A Comprehensive Solution for Effective Blood Donation and Distribution. *Available at SSRN 5101305*.

Solovyev, R., Kalinin, A. A., & Gabruseva, T. (2022). 3D convolutional neural networks for stalled brain capillary detection. *Computers in biology and medicine*, *141*, 105089.

Song, D., Zhai, Y., Tao, X., Zhao, C., Wang, M., & Wei, X. (2021). Prediction of blood supply in vestibular schwannomas using radiomics machine learning classifiers. *Scientific Reports*, *11*(1), 18872.

Suessner, S., Niklas, N., Bodenhofer, U., & Meier, J. (2022). Machine learning-based prediction of fainting during blood donations using donor properties and weather data as features. *BMC Medical Informatics and Decision Making*, *22*(1), 222.

Talukdar, B., & Bhattacharya, P. (2025). Novel aspects in blood transfusion–From donor to patient. *Journal of Hematology and Allied Sciences*, *5*(1), 18-25.

Twumasi, C., & Twumasi, J. (2022). Machine learning algorithms for forecasting and backcasting blood demand data with missing values and outliers: A study of Tema General Hospital of Ghana. *International Journal of Forecasting*, *38*(3), 1258-1277.

Upadhyay, V., Yoon, Y. M., Vazquez, S. E., Velez, T. E., Jones, K. D., Lee, C. T., ... & Shum, A. K. (2024). Phage Immunoprecipitation-Sequencing Reveals CDHR5 Autoantibodies in Select Patients With Interstitial Lung Disease. *ACR Open Rheumatology*, *6*(9), 568-580.

Vinkenoog, M., van Leeuwen, M., & Janssen, M. P. (2022). Explainable haemoglobin deferral predictions using machine learning models: Interpretation and consequences for the blood supply. *Vox Sanguinis*, *117*(11), 1262-1270.

Waheeb, R. (2024). Improving Healthcare Centers' Risk Management by Using AI. *Available at SSRN 4862674*.

Wang, S., Ono, R., Wu, D., Aoki, K., Kato, H., Iwahana, T., ... & Liu, H. (2024). Pulse wave-based evaluation of the blood-supply capability of patients with heart failure via machine learning. *BioMedical Engineering OnLine*, *23*(1), 7.

Wang, Y., Chen, Z., Lu, Y., Yang, L., Xu, T., Wu, H., ... & He, L. (2023). A review of application, modification,

and prospect of melamine foam. Nanotechnology Reviews, 12(1), 20230137.
Yang, W. H., Chan, Y. H., Huang, C. P., & Chen, T. J. (2024). Comparative analysis of GPT-3.5 and GPT-4.0 in Taiwan's medical technologist certification: A study in artificial intelligence advancements. *Journal of the Chinese Medical Association*, *87*(5), 525-530.