

Artificial Intelligence in Hemovigilance: Advancing Blood Safety and Monitoring Systems

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ABSTRACT

Blood transfusion is one of the key practices in making sure that the safety of the patients remains intact; however, traditional systems are being faced with a substantial number of challenges, such as underreporting utility of data integration issues and slow response time. Artificial Intelligence (AI) technology brings new light in dealing with these problems by means of the integration of advanced information systems that could differentiate, find out, and report the transfusion cases. This review discusses the potential of emerging AI in advancing hemovigilance by way of integrating natural language processing to support data integration, machine learning models for the detection of adverse events, and predictive analytics for personalised risk management. AI technologies are further implemented in the supply chain to improve the blood supply by the application of optimisation techniques of demand forecasting and waste reduction. It is important to note that even though hemovigilance systems' AI-based solutions ensure safe patient care and efficient operation, there are always some problems faced by AI-based technologies, for example, data privacy, algorithmic biases, and inadequate regulatory frameworks, which might cause unnecessary obstructions. In the future, effective privacy-enhancing methods will be developed, like federated learning, in addition to Explainable AI (XAI) for the human building of robust, transparent, and secure AI hemovigilance systems. This review stresses that AI will play a vital role in the future of transfusion by improving the safety and efficiency of medical services eventually.

Keywords: Blood Supply Chain Management, Machine Learning, Predictive Models, Natural Language Processing, Electronic Health Records.

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INTRODUCTION

Hemovigilance is a system composed of several components and has been developed to secure the transfusion process from the beginning to the end, which includes monitoring adverse reactions of patients to blood transfusion initially (Vuk *et al.*, 2023). It is an important element of transfusion medicine, which provides information on the areas of safety that are lacking and the potential for interventions aimed at improving patient outcomes (Chung *et al.*, 2015). Despite this, classical hemovigilance systems are confronted with serious issues such as the underreporting of adverse events, the disparity in the definitions of data, and the grading systems, which make it difficult to compare the data (Vuk *et al.*, 2023). Manual reporting and the slow response times are obstacles to the effectiveness of the systems. The measures taken to address these issues, such as the implementation of transfusion practitioners and the promotion of teamwork in the hospital

transfusion committees, have yielded some positive results (Miller *et al.*, 2015). The introduction of AI in the healthcare sector is now thus changing the way transfusion medicine is practiced. The AI technologies, consisting of Machine Learning (ML) and deep learning algorithms, offer creative tools for automatic data analysis and increased diagnostic accuracy (Yadav *et al.*, 2024). In laboratory medicine, AI applications cover the areas of operational decision-making, automation of workflows, error detection, prediction, and interpretation of results (Haymond & McCudden, 2021). The potential of these advances to revolutionize hemovigilance is enormous, by increasing the efficiency of identifying adverse events, optimizing treatment plans, and, in the long run, making transfusion medicine safer for patients (Miller *et al.*, 2015).

OBJECTIVE AND SCOPE OF THE REVIEW

This review aims to explore the integration of AI in hemovigilance systems, showing its potential to relocate to the field of blood transfusion safety rather than to its detection of adverse events and optimization of the blood supply chain. The area of study includes the exploration of AI-powered innovations



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like ML, natural language processing, and predictive analytics, besides touching upon issues like data privacy, algorithmic biases, and regulatory frameworks. The review dives into the AI's ability to bring a real revolution to transfusion medicine and the so-called safer, more efficient healthcare practices.

METHODOLOGY

This narrative review was conducted in order to explore the impact of AI on hemovigilance, referencing its function in the fields of safety, efficiency, and accuracy of blood transfusion monitoring and adverse event detection. The review combines the recent progress in AI technologies like ML, natural language processing, and predictive analytics and their application in strategies for improving hemovigilance systems. The research was based on the extensive analysis of the related studies, case studies, and the AI-driven innovations that have been conceived to estimate the benefits and drawbacks of introducing AI into the practices of transfusion medicine.

Literature search strategy

A review was carried out to search for scientific literature from reliable databases such as PubMed, Scopus, IEEE Xplore, Web of Science, Google Scholar, and Embase. Several combinations of keywords were adopted to retrieve relevant material, for instance, "Artificial intelligence in hemovigilance," "AI in blood transfusion safety," "Hemovigilance and machine learning," "AI applications in healthcare safety," "Predictive analytics in hemovigilance," and "Artificial intelligence in adverse event detection." These search items were selected to cover related studies, including AI's role in the improvement of blood transfusion safety, adverse event reporting, and operational efficiency within hemovigilance systems.

Timeframe and selection criteria

Based on the titles and abstracts labels, AI hemovigilance-related studies were picked out and went through a full-text review. Studies published from 2010 to 2024 that were peer-reviewed, reviews, and case studies about AI applications in hemovigilance, adverse event detection, and blood transfusion safety were considered. In the selection process, out of the list, we got rid of non-peer-reviewed sources, grey literature, conference abstracts, and the studies that were unrelated to AI, hemovigilance, and healthcare applications.

Data Extraction

Relevant data extracted from chosen studies includes, Study Characteristics, such as authors, publication year, study design (case study, review, experimental study), and geographical region, AI Applications, specifying featured technologies such as (e.g., ML algorithms, deep learning, natural language processing) and their role in improving blood transfusion safety and adverse event reporting; and results, which show the AI impact on adverse

event detection, reporting automation, predictive analytics, and the accuracy of hemovigilance monitoring.

REVIEW

Transforming hemovigilance with ai innovations

AI in monitoring of hemovigilance has led to a large advancement in the aspect of blood transfusion safety and operational efficiency being enhanced. While AI technologies supply different advanced features across the hemovigilance system, problems with data collection, adverse event detection, predictive analytics, and supply chain management.

Seamless data collection and integration in hemovigilance

AI has become a revolutionary instrument in hemovigilance, especially in overcoming the problems of collecting and integrating data. The key aspect of this progress is the employment of Natural Language Processing (NLP) techniques, which make it possible to handle unstructured data from Electronic Health Records (EHRs) and other sources. Unstructured clinical narratives in EHRs provide extensive and patient-specific data that are necessary for hemovigilance. NLP-enabled AI systems can pull this data out and examine it rapidly; thus, the discovery of transfusion-related incidents and other main hemovigilance indicators becomes possible (Li *et al.*, 2022). AI plays a pivotal role in hemovigilance, not only facilitating data collection but also linking and harmonising this data across different sources through the introduction of NLP, which is necessary for the analysis of unstructured data. For example, NLP techniques have been successfully utilised to detect adverse drug reactions from paediatric EHRs through the pairing of drug-symptoms with regulatory repository resources like the FDA's Adverse Event Reporting System (Wen *et al.*, 2019). Pointing out the methods that result in a breakthrough of AI in terms of data extraction and integration through the use of techniques. The evolution of high-tech, clinical language models has also completely changed hemovigilance data processing. Models like GatorTron, which have been trained on de-identified generated text sourced from over 82 billion words, have achieved near-perfect performance for a wide array of clinical NLP tasks, including concept extraction and medical question answering, to a high degree. These strengths are useful for AI mode to dig into the details, find the pertinent facets of information, and develop the most relevant data from bulk; thus, hemovigilance can be efficiently maintained to a considerable extent (Stainsby *et al.*, 2006).

Enhanced detection and reporting of blood products-induced adverse events through AI

AI and ML have served as tremendous means for the identification and notification of adverse events related to blood transfusions as well as for the general hemovigilance. ML models are utilised to

predict outcomes, assess risks, and detect complications such as haemorrhage in trauma patients that require transfusions. These models have exhibited notable qualities over traditional standards by enhancing predictions of mortality and the development of patient-specific scoring systems. AI-driven ML technologies are moving progressively to become a tool in trauma management that aids doctors in coming up with a patient-specific diagnosis (Lopes *et al.*, 2023). Existing national hemovigilance systems, such as the NHSN Hemovigilance Module in the United States, play an important role in monitoring transfusion-related adverse events. However, although these systems are not AI-based, their comprehensive databases provide the data that can be used for ML analysis, which will increase the accuracy and efficiency of adverse event detection. Also, resources like the Notify library import hemovigilance data to be used for both educational and reference purposes, therefore being very supportive of safety in transfusion practices (Huang *et al.*, 2021). Despite the advancements, the following weaknesses exist: the majority of the ML research on hemovigilance and trauma care is retrospective in nature, with little validation in real-world clinical settings, either prospective or ongoing. Even though prediction models are available for transfusion requirements and coagulopathy, they are not widely used in clinical practice, which is an indication of the theory-practice gap (Huang *et al.*, 2021).

Leveraging predictive analytics for risk management in hemovigilance

AI has the capability to be a game changer in hemovigilance programs through predictive analytics and personalized risk assessments, which in turn improve the safety of the patient and transfusion practices. Through the processing of vast arrays of data consisting of patient's background information, transfusion histories, and adverse event reports, AI-based predictive algorithms can map out intricate patterns and risk factors connected to transfusion reactions (Rana & Shuford, 2024). These revelations serve as stepping stones towards the early identification of high-risk individuals, thereby equipping clinicians with the power to put in place specific preventive measures. AI models, for example, can predict the likelihood of the most common reactions such as the febrile non-hemolytic transfusion reactions or allergic responses, therefore enhancing the application of proactive care strategies (Ramírez, 2024). AI-based decision support systems have the potential to integrate patient-specific data with clinical guidelines and risk stratification tools, which, in turn, allow for the individualisation of transfusion plans. The systems suggest data-driven best practices for the choice of blood components, the assessment of the need for medication before the transfusion, and the development of monitoring protocols suitable for personalisation. The risk of serious complications, such as Transfusion-Associated Circulatory Overload (TACO) and Transfusion-Related Acute Lung Injury (TRALI), which are potentially fatal, is diminished as this level of personalization

is implemented (Peng *et al.*, 2023). Besides these individual strategies result in increased safety of the transfusion process, they also provide the method to the efficient use of resources and the reduction of healthcare costs (Ben Elmir *et al.*, 2023).

Optimising blood supply chain efficiency with AI integration

AI has become a groundbreaking technology in blood supply chain management, with better demand forecasting, reduction in waste, and safety and traceability becoming easier as results. AI-based decision support systems that use machine learning and time series forecasting models can be the best ones in all the blood supply chain processes. This might mean things like how much you will need, how you deal with a donor, or the fixed blood donor schedules that together bring to the table heightened blood collection, reduced inventory wastage, and eliminated shortages (Joel *et al.*, 2024). The sophisticated inventory models and AI algorithms contribute to better blood inventory management, however, management practices are more important compared to the most cutting-edge tech, according to the latest research. For example, incorporating ploys of commercial supply chains like stock sharing or lateral transshipment due to expiring blood units between hospitals can incredibly boost the entire supply chain as a whole (Li *et al.*, 2022). The mashup of AI together with upcoming technologies like blockchain only further ignites the possibility of blood supply chain management. Blockchain provides means of increasing transparency, traceability, and security, thereby mitigating the potential risks like errors or fraud that may occur during the donation-to-transfusion process (Sadri *et al.*, 2021). Globally, during the COVID-19 pandemic, AI-based multivariate time-series deep learning models have proven to be effective enough to predict the demand for donations and maintain a satisfactory inventory level, hence allowing the continuous delivery of patient care (Durgun, 2024).

AI technologies transforming hemovigilance practices

AI increases efficiency in hemovigilance by using machine learning algorithms such as SVM, Random Forest, and Neural Networks which are extensively used in the health sector for pattern and anomaly detection in huge datasets from transfusion records or medical IoT devices (Hamidi *et al.*, 2021). Random Forest is the algorithm, which is noted for its resilience and great performance in different areas of application and is also the algorithm that is used in the healthcare domain. It is very effective when dealing with data sets that have a high number of features and is less likely to overfit compared to other algorithms (Bhatnagar *et al.*, 2019). SVMs are especially useful for classifying objects in the medical record and for anomaly detection and can deliver solutions with less training data (Abdullahi *et al.*, 2022). Furthermore, neural networks with their deep learning capabilities are well-suited for the discovery of concrete patterns in the very large dataset,

and as a result of such patterns, they are the key technology for hemovigilance (Arora *et al.*, 2016). For the processing of the large numbers of data that are generated by the medical IoT devices and the transfusion records, big data analytics frameworks such as Apache Spark are the only viable solutions, and they enable the processing of the datasets to be distributed (Santoro *et al.*, 2024). The addition of techniques that involve dimensionality reduction and feature extraction will give you more tools for the proper handling of high-dimensional medical data (Nunavath & Goodwin, 2019). Moreover, IoT devices with edge computing capability are able to conduct real-time monitoring during transfusions, and thus anomalous events will be immediately detected and assist in the increase of the patient's safety. The employment of these AI-driven techniques in combination ensures that the hemovigilance systems can be highly effective in monitoring and improving transfusions (Akingbola *et al.*, 2024).

Real-world applications and case studies of AI in hemovigilance

The incorporation of AI in hemovigilance has emerged as a feasible strategy to enhance healthcare outcomes and the credibility of adverse event reporting in the systems. Take, for example, a study that used the FDA Adverse Event Reporting System (FAERS) database AI's ability to detect safety signals in new drugs such as lumateperone. This analysis detected 125 adverse event signals among 26 System Organ Classes, comprising 108 previously unknown signals, thereby confirming the potential of AI to detect security issues that do not appear to be clear but are hidden in real-world data (Fatima *et al.*, 2024). Moreover, one of the most ingenious uses of AI is demonstrated through DeepSAVE, which is a deep learning framework designed to precisely identify user query logs that contain adverse events. It presented a solution to the problem of comprehension in the diverse search settings and the variety of user behaviour levels. In contrast to the available

methods, DeepSAVE led in achieving the best results while it was used in three vast authentic datasets, thus supporting the fact that AI has the power to utilise the online search data for quick learning of potential adverse events (Olawade *et al.*, 2024). The AI safety monitoring assistance in educational situations has been put under investigation. A research project that involved health science students who participated in AI-enhanced simulations discovered that the intervention group reported more medication-related adverse events than the control group. The results of this study suggest that AI-based simulations are capable of enhancing the ability of the participants to think systemically and accurately report, thus resulting in the practice of the safety monitoring and reporting processes (Khalifa & Albadawy, 2024). In spite of the promises brought by the development, some issues still remain to be cracked regarding the use of AI for adverse event detection (Alowais *et al.*, 2023).

DISCUSSION

AI technologies in hemovigilance are now ensuring enhanced safety, efficiency, and accuracy from the transfusion processes of blood through the implementation of the new operations. AI-enabled predictive analytics and decision support systems have been shown to mainly impact their features to foresee the possible safety problems in advance and then accordingly raise the patient's outcome. Using patient records collected over a wide area of past cases, these systems are able to uncover unseen patterns and risk factors and thereby lead to proactive interventions and the development of personalised transfusion strategies (Alowais *et al.*, 2023). Besides, the AI algorithms applied to medical imaging have likewise improved their diagnostic precision by allowing rapid and accurate evaluation of blood transfusion-related complications. On the one hand, AI offers its promise; on the other hand, traditional hemovigilance practices still persist (Figure 1). Research studies have proved the transfusion reaction rates that

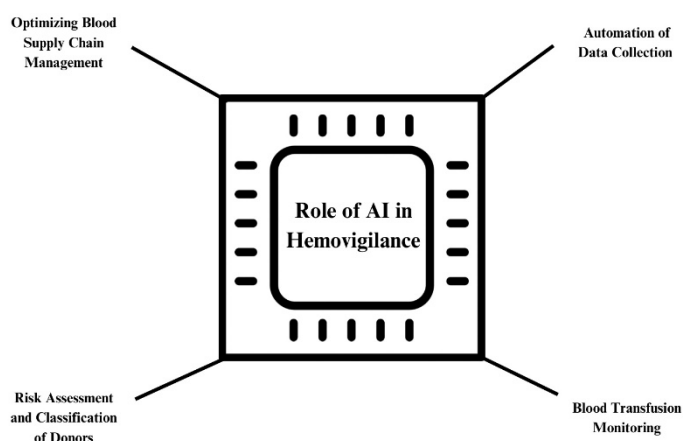


Figure 1: Role of AI in Hemovigilance. This figure illustrates the integration of artificial intelligence tools in the monitoring and reporting of adverse events in blood transfusion practices, highlighting the potential for predictive analytics and automated data processing in improving patient safety. At column width.

range from 0.27% up to 0.3%, thereby emphasising the necessity for constant and vigilant supervision (Gala *et al.*, 2024). The most frequent reactions reported were allergy, febrile non-haemolytic transfusion reaction, and acute haemolytic reaction (Maleki Varnosfaderani & Forouzanfar, 2024). This information portrays the necessity to continue involving brilliant AI functions along with traditional ways; hence, the thorough inspection and patient protection will be achieved (Waheed & Liu, 2024). The inclusion of AI in hemovigilance systems prompts many benefits, like the prompt determination of events, the decision-making processes through evidence-based knowledge, and the simplification of monitoring. The issues like data protection issues, algorithmic biases, and the absence of strong regulatory frameworks need to be overcome in order to take advantage of AI fully. As AI technologies improve and express partnership with traditional hemovigilance methods, the safety blood monitoring system will be more robust and effective; hence, better transfusion practices and health care outcomes could be introduced (Meher, 2024).

The integration of AI and Explainable AI (XAI) in healthcare is faced with many issues that need to be improved to make it effective. One of the key points is to ensure transparency and the ability to integrate with the existing healthcare infrastructure. In the future, AI might become more widely used in crucial areas such as healthcare if it is able to provide accurate and comprehensible explanations of its decisions and predictions. Nevertheless, the complexity of deep learning models often leads to "black box" systems, which underscores the requirement for developing AI models that are more interpretable and transparent (Olawade *et al.*, 2024). This aspect is particularly important in the medical domain because AI-generated errors may lead to disastrous results. The privacy of patients and the security of their data are other significant issues. The implementation of AI requires the use of strong measures to protect healthcare data from breaching at the same time being in compliance with regulatory and ethical standards (Durgun, 2024). Adequate consent management and adherence to cybersecurity protocols play a vital role in promoting patient autonomy and maintaining the integrity of data. To solve these problems, first and foremost, we need clear regulatory frameworks and transparent validation processes of AI models. Besides, the creative process of cybersecurity, and ethical policies should be worked out to introduce the AI systems in a proper way. Moreover, universal standards for interoperability and equal access to AI technologies are mandatory to avoid inequalities in medical treatment (Bhatnagar *et al.*, 2019). The cooperation between healthcare professionals, policymakers, and researchers is required; thus, it will stimulate interdisciplinary innovations and help AI technologies become a part of the clinical practice (Alowais *et al.*, 2023).

EMERGING TRENDS AND FUTURE PROSPECTS OF AI IN HEMOVIGILANCE

The future of AI in hemovigilance and healthcare relies on the creation of standards that incorporate the integration of AI with other systems and exercising of privacy-protective techniques such as federated learning (Huang *et al.*, 2021). Federated learning is a new way that enables the privacy of data while AI models are improved. This technique enables the training of the neural networks in remote distributed edge devices in a collaborative manner by avoiding the case of passing the raw data. Consequently, patient details confidentiality is maintained, and privacy regulations like GDPR and HIPAA are met (Abdullahi *et al.*, 2022). It aids in the establishment of a healthcare open ecosystem by enabling knowledge sharing to be done from widespread and varied data sets but with privacy being maintained (Arora *et al.*, 2016). However, federated learning has both advantages and weaknesses, with the drawbacks being the distortion of the model due to the channel fading and poor aggregation of locally trained models on the unbalanced data (Maleki Varnosfaderani and Forouzanfar, 2024). Further development in the future might be achieved by combining digital twin technology with federated learning, which could shape smart city healthcare network applications. Besides federated learning, global AI standards in hemovigilance and healthcare should be implemented (Waheed and Liu, 2024). Consistency, interoperability, and fairness will be the main guarantees of these standards, while at the same time they will guarantee the security of trust and the acceptance of them clinically. The incorporation of AI in different datasets and the automation of workflows would even make AI more valuable in hemovigilance programs. Hence, AI's growing role evolves; the problems of generalising algorithms, validating the clinical procedures, and integrating advanced technologies such as large language models will be of utmost importance in the healthcare delivery transformation (Meher, 2024).

LIMITATIONS

AI-powered surveillance of blood transfusions is hindered by improper and inadequate data, which causes the wrong forecast. As it predominantly depends on existing templates, it encounters difficulties in tracking down rare or novel adverse events. Despite the fact that the methods differ from one research to another, the participants and the controls should be the same; the methodologies have to be uniform, which tells us clearly that the protocols are mismatched. AI technologies also cannot easily account for the individual patient characteristics that complicate the transfusions, like comorbidities and genetics, as they require human interaction in such cases where transfusion reactions are affected. Furthermore, the systems may grow outdated and thus not function properly in COVID-19-related transfusion safety applications if these machines do not receive continuous updates and a steady flow of medical inputs.

CONCLUSION

Healthcare reached a whole new level thanks to artificial intelligence, which in return improved the decision-making process, diagnostics, and patient management. In the context of hemovigilance, artificial intelligence becomes a powerful qualitative and quantitative tool that contributes to the improvement of the monitoring and reporting of transfusion-related adverse events with its advanced data analysis and pattern recognition. Nevertheless, successful application is the hard part we must overcome due to the problems we may face in relation to issues of data availability, digital infrastructure, ethics, and regulatory compliance, particularly in less developed regions. Collaboration among them is crucial while the right use of AI is ensured. It can lead to a transparent, secure, and patient-focused hemovigilance framework. With time, AI-based technologies can help create a more continuous and more inclusive health practice. Hemovigilance can be strengthened through an equitable, tempered approach addressing technical, ethical, and operational challenges, thus assuring the development of new practices and enhancing patient security in transfusion medicine.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ABBREVIATIONS

AI: Artificial Intelligence; **ML:** Machine Learning; **NLP:** Natural Language Processing; **EHR:** Electronic Health Record; **XAI:** Explainable AI; **TACO:** Transfusion-Associated Circulatory Overload; **TRALI:** Transfusion-Related Acute Lung Injury; **FAERS:** FDA Adverse Event Reporting System.

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