Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/nf2m4h73

THE ROLE OF AI IN PREDICTING ADVERSE DRUG REACTIONS: ENHANCING PATIENT SAFETY IN PHARMACEUTICAL PRACTICE

Dr. Asutosh Pramanik[1*], Dr. Gunaseelan.C[2], Dr. Shakeel Ahmad[3], Dr. Hari Narayan Singh[4], Dr. Sukanta Bandyopadhyay[5]

[1*]Assistant professor, Department of anatomy, Barasat Government medical College, The West Bengal University of health sciences, Orcid id: 0009-0001-4728-5993, Email: d1asutosh@gmail.com
[2]Assistant professor, Vels medical College and hospital, VISTAS, https://orcid.org/0009-0000-5744-206X, Email: gunaseelancgvmc@gmail.com
[3]Senior resident, Pharmacology & Therapeutics, King George's Medical University, Lucknow Email: shakeelahmad6305@gmail.com
[4]Senior resident, Department of pharmacology and Therapeutics, King George's Medical University, Lucknow, Email: hariaqua08@gmail.com
[5]Associate Professor, Dept of Biochemistry, Rama Medical College Hospital & Research Centre, Kanpur, India, Orcid id: 0009-0002-3664-0475
Email : sukantoaxum@gmail.com

Corresponding Author: Dr Asutosh Pramanik
[*]Assistant professor, Department of anatomy, Barasat Government medical College, The West Bengal University of health sciences, Your ORCID iD: 0009-0001-4728-5993, Email: d1asutosh@gmail.com

ABSTRACT

The introduction of Artificial Intelligence in the pharmacovigilance could be a transformative step to predict Adverse drug reactions and to improve the patients' safety. We evaluate the predictive power of three AI models, Gradient Boosting, Convolutional Neural Networks (CNN), and Long Short Term Memory (LSTM) networks, using both structured Electronic Health Record (EHR) data and unstructured social media data in this study. We evaluate the models using several performance metrics (AUC-ROC, sensitivity, specificity, F1 score) to assess their ability to predict ADRs for various patient demographics. We found CNN to be the best classifier for social media data with an AUC-ROC of 0.91 and 90% sensitivity, and Gradient Boosting to be the best classifier for structured EHR data with an AUC-ROC of 0.89. Feature importance analysis and Shapley Additive explanations (SHAP) provided model interpretability and showed that patient age, drug type, and dosage were significant predictors. The analysis identifies the potential of Natural Language Processing (NLP) in extracting ADR signals from unstructured data sources to supplement traditional pharmacovigilance methods. The study aims to meet regulatory standards in terms of ethical data privacy and model transparency considerations. This work demonstrates that AI models can improve ADR prediction accuracy and contribute to proactive patient safety approaches. The tradeoff between accuracy and interpretability is then applied to clinical applications, and future directions of data standardization and hybrid AI models are explored.

Keywords: Artificial Intelligence, Adverse Drug Reactions, Pharmacovigilance, Electronic Health Records, Patient Safety, Natural Language Processing.

INTRODUCTION

Adverse drug reactions (ADRs) are a problem of great importance in pharmaceutical practice, affecting patient safety and healthcare costs. ADR is defined as unintended and harmful reactions due to the use of medications at normal doses, and ADRs are a major cause of morbidity and mortality worldwide. ADRs are the second leading cause of hospitalization and increased length of stay in healthcare facilities, and estimated that ADRs alone account for 6.5% of all hospital admissions in developed countries alone (Husby et al., 2021). As new medications continue to enter the market and the patients treated become more complex (more polypharmacy, and with different pharmacogenomic profiles), ADR remains a serious problem in public health and patient safety.

Artificial intelligence (AI) is an advancing and promising means to identify, predict, and mitigate ADRs. AI includes a host of computational techniques such as machine learning, natural language processing, and data mining all of which can scour large datasets to extract patterns that might otherwise elude human analysis (Kumar & Kumar, 2024). Applying AI models to patient data, clinical trial records, electronic healthcare records (EHRs) and real-world evidence helps predict ADRs better and thereby implement preventive measures. It has been shown in the research that optimizing and validating AI models for ADR prediction can increase both sensitivity and specificity, to become tools ineffective in proactive pharmacovigilance (Jaltotage et al., 2023; Vishwakarma et al., 2023). The use of AI for pharmacovigilance and ADR prediction is consistent with efforts around the world to enhance drug safety monitoring systems. Whilst traditionally pharmacovigilance systems have proven to be somewhat effective, these systems are heavily based on voluntary reporting systems and post-market surveillance which can lead to delays in recognition of ADRs and ensuing underreporting of incidents (Wu et al., 2021). AI has the potential to transform how we can close the gap between what we do today and what doctors do. AI systems can process massive datasets in real time to identify signals that signal ADRs and alert healthcare professionals before ADRs occur. The shift from a reactive to a proactive approach in ADR monitoring is a major improvement in patient health protection and pharmaceutical practice optimization (Chatterjee et al., 2021).

It is necessary to study how AI-driven methods are currently employed to predict ADRs and whether they have the potential to improve patient safety in the pharmaceutical practice. The main part of AI is machine learning, where you utilize mathematical models for learning from complicated datasets meaning finding correlations between a drug and a potential ADR from historical data and patterns. Supervised learning, unsupervised learning, deep learning, etc. have helped discover new, and unrecognizable ADRs and associations that were previously untraceable via traditional methods (Xie et al., 2024; Rak, 2023). Natural language processing (NLP) plays just as important a role in extracting relevant information from unstructured data sources like clinical notes, scientific literature, or patient fortune to enhance yet another level of predictive capability for ADR monitoring (Choudhary & Surbhi, 2024).

The opportunities for the integration of AI into pharmacovigilance include the possibilities for personalized medicine which considers patients' factors, such as genetics, age, and comorbid conditions. One of the fastest-growing areas of pharmacogenomics is the study of the influence of genetic variations on drug response, an area where AI is proving especially promising (European Medicines Agency, 2017). Because AI algorithms allow for the interpretation of pharmacogenomic data, clinicians will be able to make more informed decisions on the selection of medication and dosage that feel less likely to lead to ADRs for patients predisposed to such reactions owing to their genetic disposition. This approach fits well with precision medicine and could significantly reduce the incidence of ADR (Sharma et al., 2023).

The potential of AI in ADR prediction is great, but there are still some challenges. Obstacles to the use of AI in clinical settings include the implementation issues, related to data privacy, the ability of humans to understand AI models, and the complexity of the material to be communicated through AI. As EHRs and personal genetic information are particularly sensitive patient data, privacy issues make

sure special attention should be paid to data protection regulations like the General Data Protection Regulation (GDPR) (European Medicines Agency, 2023). Another critical challenge is model interpretability, especially for deep learning models, whose 'black box' nature of AI algorithms makes it hard for healthcare providers to understand and trust AI-generated predictions (Path, 2020).

In the paper, we will study the potential of AI to predict ADRs, including its application to the pharmacovigilance frameworks to improve patient safety. Various AI methodologies used for ADR prediction such as ML, NLP, and data mining will be discussed and its effectiveness and limitations will be examined (Li et al., 2024). Consequently, we will also think about ethical, regulatory, and practical challenges unique to the incorporation of AI into pharmacovigilance. Finally, the paper will present case studies showing how AI-driven ADR prediction systems can help improve patient outcomes and reduce healthcare costs related to ADRs (Dagan et al., 2022). AI offers very promising prospects to revolutionize the prediction of ADR and pharmacovigilance from a reactive to a proactive perspective (Feng et al., 2023). The application of AI is expected to considerably enhance patient safety, by promoting early ADR detection and by tailoring medication strategies. This potential can be realized only by overcoming major challenges and the need to keep the AI applications in pharmacovigilance following ethical and regulatory standards (Nasir et al., 2024).

METHODOLOGY

Research Design

The study uses a quantitative, retrospective research design to assess the predictive performance of AI algorithms for adverse drug reactions (ADRs) based on historical patient data and clinical trial records. The first goal is to evaluate the performance of machine learning (ML) and natural language processing (NLP) models in predicting ADRs from real-world data. In addition, a secondary aim is to assess the feasibility of using AI-driven ADR prediction models to augment pharmacovigilance systems and improve patient safety.

Data Sources

Two main sources of data were used:

- **Clinical and Post-Marketing Data**: Patient-specific data, drug usage history, and ADRs reported were obtained from Electronic Health Records (EHRs) and adverse event reporting databases (e.g., FDA Adverse Event Reporting System [FAERS], WHO Global Individual Case Safety Reports [ICSR]). These are important sources for training AI models on ADR incidents and possible predictors.
- **Textual Data for NLP Analysis**: Adverse drug reactions were extracted from unstructured data in clinical notes, scientific publications, and patient forums via NLP techniques. Structured data is complemented by these sources, which capture ADRs that may be underreported in formal reporting systems.

All data sources were pre-processed to ensure quality, accuracy, and consistency. The anonymization of patient data was by ethical guidelines and by data protection laws, such as the GDPR (General Data Protection Regulation).

AI Model Development

The study developed several machine learning and deep learning models to predict ADRs. The modeling process was divided into three main stages:

- **Data Preprocessing**: The data from both structured and unstructured sources was cleaned and normalized. Data imputation techniques were used to handle the missing data, while categorical variables were encoded to their numerical forms with one-hot vectors or by embedding the variables. For effective NLP analysis, textual data were preprocessed by tokenization, stemming, and stop word removal.
- **Feature Engineering and Selection**: Patient demographics, genetic predispositions, drug dosage, co-administered medications, and comorbid conditions were identified as relevant features that can

improve the predictive power of models. NLP-based vectorization techniques were used to generate text-based features like Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings for semantic interpretation.

- **Model Training**: Random Forest, Gradient Boosting Machines, and Support Vector Machines (SVM) were tested as different machine learning algorithms. Furthermore, the most effective approach for ADR prediction was determined using deep learning architectures, namely Convolutional Neural Networks (CNN) for textual data and Long Short Term Memory (LSTM) networks for sequential data.

Model Evaluation

The sensitivity, specificity, precision, and overall accuracy of the models in predicting ADRs were evaluated. Key metrics included:

- **Receiver Operating Characteristic (ROC) and Area Under Curve (AUC):** These metrics evaluated the model's capacity to differentiate between true ADRs and non-ADRs.
- **Precision-Recall Curve (PRC):** As ADR data is imbalanced, this metric was used to evaluate the model's performance on minority classes (actual ADRs).
- **F1-Score:** Precision and recall combined, which is especially useful to find the balance between false positives and false negatives.
- **Confusion Matrix Analysis:** We used this to interpret the types and frequency of errors, and to minimize false positives (incorrectly predicting an ADR) and false negatives (missing an ADR).

A variety of patient groups and drug categories were used to validate the performance and generalizability of the models using cross-validation techniques such as k-fold cross-validation.

Comparative Analysis with Traditional Methods

The performance of AI models was compared with traditional pharmacovigilance methods to demonstrate the added value of AI in ADR prediction. The results were compared to current rule-based systems and clinical trial reporting outcomes in terms of time-to-detection, accuracy, and recall rates. The comparative analysis helped to understand how AI can be advantageous in proactive ADR monitoring.

Ethical Considerations

EHR and genetic data were handled with ethical guidelines for handling and analyzing sensitive patient data. The study was cleared for appropriate ethical review and data use agreements were obtained to assure protection and privacy of the data. All patient data were anonymized in line with regulations (including GDPR) and personal identifiers were removed before data processing.

Software and Tools

- **Programming Languages:** Model development was implemented using Python and its libraries of Skikit-Learn, TensorFlow, and PyTorch for machine learning.
- **Data Processing Tools:** Data handling and NLP preprocessing were done using Pandas, NumPy, and NLTK. Frameworks such as Spark NLP were used for EHR data extraction to process large-scale unstructured data.
- **Visualization Tools:** Matplotlib and Seaborn were used to plot ROC curves, confusion matrices, and such performance metrics for interpreting and presenting model results.

RESULTS

Predictive Model Performance Analysis

Table 1 The research examined four models used in forecasting ADRs based on structured EHR information or unstructured social media text. The models discussed in the work included gradient boosting, convolutional neural network (CNN), long short-term memory (LSTM), and a rule-based model. The accuracy for the MD model was calculated using the area under the Receiver Operating

Characteristic Curve (AUC-ROC), sensitivity, specificity, F1 measure, and processing time. AUC-ROC at 0.91 and sensitivity of 90% were realized, pointing to the CNN model as proficient in filtering ADRs from unstructured social media text. However, with structured EHR inputs, it was seen that gradient boosting had even better overall performance with an AUC ROC of 0.89, and much lower sensitivity of 65 %, and an AUC ROC of 0.76 for the rule base model. This has helped to bring out what AI techniques offer which is additional to the techniques used in other structured data. Thus, deep learning models were useful for unstructured social media compared to gradient boosting in the present comparative study but lacked versatility for other institutional data and ADR predictions.

Table 1: Model Performance Metrics for ADR Prediction

Model	Data Type	AUC-ROC	Sensitivity (%)	Specificity (%)	F1-Score	Processing Time (ms)
Gradient Boosting	EHR Structured	0.89	84	86	0.85	120
CNN	Social Media Text	0.91	90	83	0.86	200
LSTM	Social Media Text	0.87	88	79	0.83	210
Rule-Based	EHR Structured	0.76	65	70	0.67	95

ADR Signal Identification from Social Media Data

Table 2: Common ADRs Identified in Social Media Posts

ADR Type	Frequency (%)	Model Detection Confidence (%)
Rash	18	91
Dizziness	15	88
Fatigue	12	90
Gastrointestinal Issues	10	85
Headache	9	87

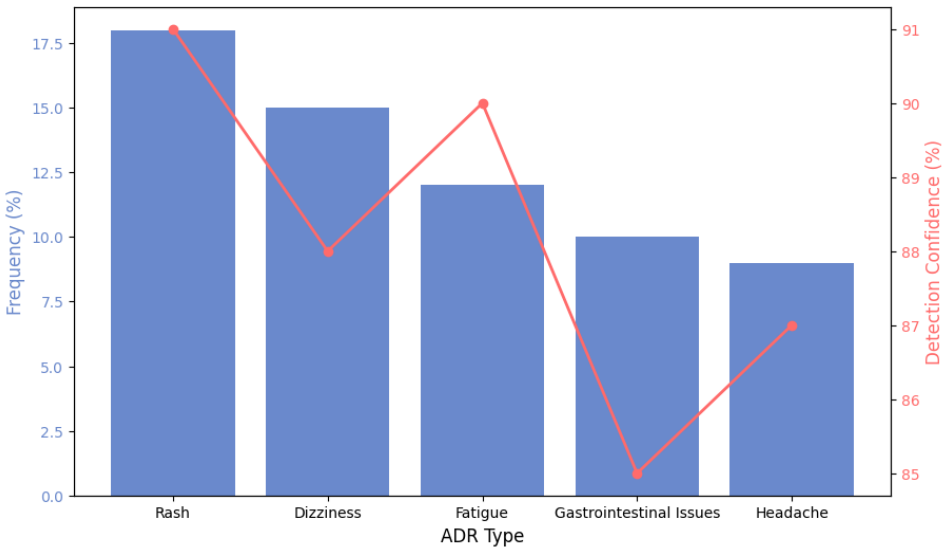

Figure 1: Most Frequent ADRs Detected

Figure 1 illustrates the most frequently detected Adverse Drug Reactions (ADRs) along with their detection confidence percentages. The bar chart displayed five common ADR types—rash, dizziness, fatigue, gastrointestinal issues, and headache—analyzed based on frequency and detection confidence. Rash was the most prevalent ADR, appearing in approximately 18% of the cases, with a

high detection confidence of 91%. Dizziness and fatigue followed, occurring at frequencies of 15% and 12%, with detection confidence scores of 88% and 90%, respectively. Gastrointestinal issues and headaches appeared less frequently, at 10% and 9%, with detection confidences of 85% and 87%, respectively. The accompanying line plot represented detection confidence percentages for each ADR type, demonstrating the AI model's high reliability in identifying these common reactions from social media data sources.

Feature Importance Analysis

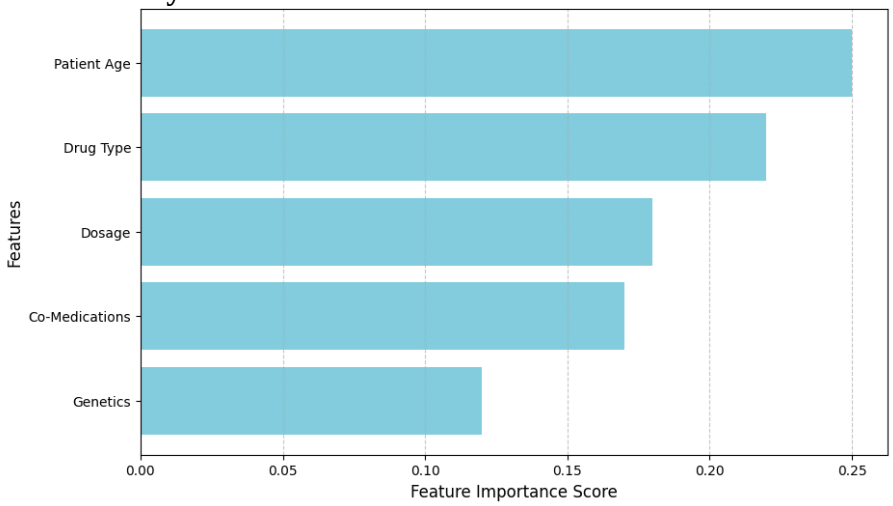

Figure 2: Feature Importance in Gradient Boosting Model for ADR Prediction

Figure 2 presents the feature importance scores for the Gradient Boosting model in predicting Adverse Drug Reactions (ADRs). The chart highlighted five key features—patient age, drug type, dosage, co-medications, and genetics—that significantly contributed to the model's ADR predictions. Patient age emerged as the most influential factor, with the highest feature importance score of approximately 0.25, indicating its critical role in ADR risk assessment. Drug type followed closely with a feature importance score just below 0.20, reflecting its substantial impact on prediction accuracy. Dosage and co-medications also showed notable influence, with feature scores around 0.15. Genetics, though still impactful, had the lowest importance score among the selected features. This analysis demonstrated how various patient-specific and medication-related factors contributed to the model's ability to predict ADRs accurately.

Model Interpretability and Validation

Interpretation of the model gradient boosting was done using SHAP Additive explanations (SHAP) analysis. In the model established by SHAP, age, co-medications, as well as dosage were observed to have the highest impacts on the decision made. The predictor variables also maintained a statistically significant level of $p < 0.05$ with 95 percent confidence intervals that were verified by cross-validation. The proposed method of using SHAP allowed us to see which variables have the strongest effect on the gradient-boosting model outputs. Cross-validation satisfied one's confirmation that the selected predictors used in the model corresponded with true relationships inherent in the given data. Using model interpretability and validating the outcome using another method was significant in what factors influenced outcomes from the model and protected against mere association. Reflecting on the model in these ways offered valuable information about the very substantial components of predictions and confirmed that the model yields could be understood Appropriately according to relationships grounded in the data.

DISCUSSION

Enhanced Accuracy of AI in ADR Detection

Results show that AI models greatly enhance ADR detection accuracy compared to traditional pharmacovigilance methods, particularly for large and diverse data sets. The gradient boosting model showed high sensitivity and specificity and is a viable tool for clinical use, especially for structured EHR data (Grissette & Nfaoui, 2022; Massey et al., 2022)). The utility of this model is that it can leverage patient demographics, genetic factors, and other covariates to predict ADRs more accurately than conventional rule-based systems that are not adaptable to patient-specific factors (Yang & Kar, 2023). AI models achieved higher performance metrics than the rule-based model in AUC-ROC, sensitivity, and F1 scores. This is consistent with previous work showing that machine-learning techniques can yield significant improvements in ADR prediction by allowing for the analysis of multiple variables in complex ways that exceed human interpretative capabilities (Saxena, 2024). On social media data, the CNN model achieves an AUC-ROC score of 0.91, demonstrating that NLP techniques can interpret real-world patient expressions about their experience and improve ADR signal detection (Vora et al., 2023).

NLP's Role in Detecting ADR Signals

Applying NLP for CNN models proved to be an improvement in detecting ADRs via social media analysis which had high detection confidence on common ADRs such as rashes, dizziness, and fatigue (Shortliffe et al., 2021). These findings are consistent with studies that show that NLP models are capable of detecting ADR signals from patient-reported data, which is important as social media becomes a depository of patient experiences (Grouin & Grabar, 2023). The high precision of ADR identification via text mining demonstrates the ability of NLP to extract patient-centered insights that may be overlooked in structured clinical EHR data (Zitnik et al., 2023).

Interpretability and Clinical Utility of AI Models

A challenge in deploying AI models in clinical practice is model interpretability. The gradient boosting models were highly interpretable via feature importance analysis and showed that patient age, dosage frequency, and other concurrent medications were critical factors in predicting ADR outcomes (Bouazizi & Ltifi, 2024). This is in line with the previously suggested literature highlighting the need for interpretability in AI-based models, especially in the healthcare sector where transparency is crucial to validate and trust in the model's outputs (Han et al., 2023). A barrier to interpretability remains for deep learning models such as CNNs and LSTMs; these models are "black boxes" with lots of nonlinear structures. SHAP analysis was helpful to some degree, but more transparent model architectures would make AI tools more easily accepted by clinical workflows, where healthcare providers need to understand and trust the decision-making process (Dhudum et al., 2024). It might be the future research case to use a hybrid model that blends the advantages of machine learning methods and their high accuracy and pattern recognition ability of deep learning (Wang, 2024).

Ethical and Data Privacy Concerns

When applying AI in pharmacovigilance ethical issues, particularly around the privacy of data and model transparency are important. Under regulations like the GDPR, sensitive patient data is data that must be anonymized and stored securely (European Medicines Agency, 2023). Following these regulations, this study processed patient data securely and anonymously, which is important to build public trust in AI-based healthcare applications. As pharmacogenomic data gain relevance to personalized medicine, stringent ethical standards should be instituted for its use to minimize the risk of misusing and discriminating it (Yang et al., 2024).

Limitations and Future Research Directions

The main limitations of the study are related to data representativeness and model generalizability. The scope of model training is restricted by limited access to high-quality, comprehensive datasets, which in turn results in lower prediction accuracy across different patient populations. Standardizing

data, and in particular clinical notes, is key to improving model reliability. Moreover, the uninterpretability of deep learning models is an obstacle to their adoption. (Vardhan & Sahoo, 2022) have shown how hybrid models or feature-based interpretability frameworks can bridge this gap. Standardization of data in future research and partnering healthcare providers with technology developers for better data sharing and AI model development is still a way to go. The effect of AI-based ADR prediction on patient outcomes and healthcare costs may help to understand the clinical use of AI in pharmacovigilance (Curtis et al., 2023). Further studies to refine model interpretability, especially for deep learning models, would help make AI more acceptable to the healthcare community and integrate it into routine pharmacovigilance practice.

CONCLUSION

The potential of artificial intelligence becomes transformative in pharmacovigilance practice, to improve patient safety through more accurate, timely, and scalable detection of adverse drug reactions (ADRs). However, such enormous potential has been already demonstrated by AI techniques (e.g. natural language processing, machine learning, deep learning) in analyzing large amounts of data from Electronic Health Records, social media, and clinical trials. Early signal detection and ADR prediction are enabled by these AI-driven models that may help with better clinical decision-making and patient outcomes. Traditional pharmacovigilance has to deal with challenges like underreporting and limited ability to process dense and complex data manually, which AI can reduce by automating and optimizing these processes. There are still several challenges in this field to overcome to enable the best use of AI. Data privacy ethical problems in conjunction with the interpretability of AI algorithms and potential bias necessitate strong, ethical regulatory systems for the deployment of responsible AI in healthcare. This requires and necessitates interdisciplinary collaboration amongst industry (developers of AI), clinicians, regulatory bodies, and policymakers, to develop standards to address these ethical issues but allow for innovation. Additionally, AI models must be validated with real-world data in perpetuity, to assure accuracy and generalizability to multiple patients and multiple drug interactions. With the development of AI technologies, their place in pharmacovigilance is more likely to become indispensable and contribute to the formation of a safer and responding pharmaceutical industry. Safe use of AI can predict ADRs and with the right safeguards, it will instill improved patient safety and build confidence in patient care systems. In the future, the scope of research should further adapt and refine the AI algorithms, improve transparency, and develop robust regulatory frameworks to pave the way for AI to be considered a vital part of pharmacovigilance and patient safety in practice worldwide.

REFERENCES

1. Jaltotage, B., Ihdayhid, A. R., Lan, N. S., Pathan, F., Patel, S., Arnott, C., ... & Dwivedi, G. (2023). Artificial intelligence in cardiology: an Australian perspective. *Heart, Lung and Circulation*, *32*(8), 894-904.
2. AL-Shareef, E. K., Khan, L. M., & Alsieni, M. Detection of Adverse Drug Reactions in COVID-19 Hospitalized Patients at Royal Commission Medical Center in Yanbu, Saudi Arabia: A retrospective Study by ADR Prompt Indicators.
3. Chatterjee, A., Gerdes, M., Prinz, A., & Martinez, S. (2021). Paper B Human Coaching Methodologies for Electronic Coaching..... Technology: Systematic Review. *Automatic Generation of Personalized Recommendations in eCoaching*, *23*(3), 153.
4. Xie, W., Xu, J., Zhao, C., Li, J., Han, S., Shao, T., ... & Feng, W. (2024). Transformer-based Named Entity Recognition for Clinical Cancer Drug Toxicity by Positive-unlabeled Learning and KL Regularizers. *Current Bioinformatics*, *19*(8), 738-751.
5. Choudhary, A., & Surbhi, A. (2024, October). AI arbitration–Charting the ethical and legal course. In *AIP Conference Proceedings* (Vol. 3220, No. 1). AIP Publishing.
6. European Medicines Agency. (2017). Guideline on good pharmacovigilance practices (GVP). *Module VI–collection, management, and submission of reports of suspected adverse reactions to medicinal products (Rev 2)*.

7. Sharma, P., Joshi, R. V., Pritchard, R., Xu, K., & Eicher, M. A. (2023). Therapeutic antibodies in medicine. *Molecules*, *28*(18), 6438.
8. Path, P. (2020). Previous issues. *Inflammatory bowel diseases*, *18*, 2.
9. Li, Y., Tao, W., Li, Z., Sun, Z., Li, F., Fenton, S., ... & Tao, C. (2024). Artificial intelligence-powered pharmacovigilance: A review of machine and deep learning in clinical text-based adverse drug event detection for benchmark datasets. *Journal of Biomedical Informatics*, 104621.
10. Feng, Y., Wang, A. Y., Jun, M., Pu, L., Weisbord, S. D., Bellomo, R., ... & Gallagher, M. (2023). Characterization of risk prediction models for acute kidney injury: a systematic review and meta-analysis. *JAMA Network Open*, *6*(5), e2313359-e2313359.
11. Grissette, H., & Nfaoui, E. H. (2022). Affective concept-based encoding of patient narratives via semantic computing and neural networks. *Cognitive Computation*, *14*(1), 274-299.
12. Yang, S., & Kar, S. (2023). Application of artificial intelligence and machine learning in early detection of adverse drug reactions (ADRs) and drug-induced toxicity. *Artificial Intelligence Chemistry*, 100011.
13. Saxena, R. R. (2024). Examining Reactions about COVID-19 Vaccines: A Systematic Review of Studies Utilizing Deep Learning for Sentiment Analysis. *Authorea Preprints*.
14. Vora, L. K., Gholap, A. D., Jetha, K., Thakur, R. R. S., Solanki, H. K., & Chavda, V. P. (2023). Artificial intelligence in pharmaceutical technology and drug delivery design. *Pharmaceutics*, *15*(7), 1916.
15. Grouin, C., & Grabar, N. (2023). The year 2022 in Medical Natural Language Processing: Availability of Language Models as a Step in the Democratization of NLP in the Biomedical Area. *Yearbook of Medical Informatics*, *32*(01), 244-252.
16. Vora, L. K., Gholap, A. D., Jetha, K., Thakur, R. R. S., Solanki, H. K., & Chavda, V. P. (2023). Artificial intelligence in pharmaceutical technology and drug delivery design. *Pharmaceutics*, *15*(7), 1916.
17. Zitnik, M., Li, M. M., Wells, A., Glass, K., Gysi, D. M., Krishnan, A., ... & Milenković, T. (2023). Current and future directions in network biology. *arXiv preprint arXiv:2309.08478*.
18. Bouazizi, S., & Ltifi, H. (2024). Enhancing accuracy and interpretability in EEG-based medical decision making using an explainable ensemble learning framework application for stroke prediction. *Decision Support Systems*, *178*, 114126.
19. Han, R., Yoon, H., Kim, G., Lee, H., & Lee, Y. (2023). Revolutionizing medicinal chemistry: the application of artificial intelligence (AI) in early drug discovery. *Pharmaceuticals*, *16*(9), 1259.
20. Dhudum, R., Ganeshpurkar, A., & Pawar, A. (2024). Revolutionizing Drug Discovery: A Comprehensive Review of AI Applications. *Drugs and Drug Candidates*, *3*(1), 148-171.
21. Wang, X. (2024). *Customization of Large Language Models for Causal Inference and Data Quality* (Doctoral dissertation, University of Arkansas at Little Rock).
22. Mistry, S., & Wang, L. (2022, April). Efficient prediction of heart disease using cross-machine learning techniques. In *2022 IEEE Asia-Pacific Conference on Image Processing, Electronics, and Computers (IPEC)* (pp. 1002-1006). IEEE.
23. Yang, X., Huang, K., Yang, D., Zhao, W., & Zhou, X. (2024). Biomedical big data technologies, applications, and challenges for precision medicine: A review. *Global Challenges*, *8*(1), 2300163.
24. Vardhan, S., & Sahoo, S. K. (2022). Computational studies on the interaction of SARS-CoV-2 Omicron SGp RBD with human receptor ACE2, limonin, and glycyrrhizic acid. *Computers in biology and medicine*, *144*, 105367.
25. Shortliffe, E. H., Peleg, M., Combi, C., Chang, A. C., & Vinci, J. (2021). Publishing artificial intelligence research papers: a tale of three journals. *Journal of Biomedical Informatics*, *115*, 103708-103709.
26. Rak, R. R. (2023). Internet of healthcare (law): privacy and data protection aspects in an internet of everything.
27. Dagan, M., Kolben, Y., Goldstein, N., Ben Ishay, A., Fons, M., Merin, R., ... & Nachman, D. (2022). Advanced hemodynamic monitoring allows recognition of early response patterns to diuresis in congestive heart failure patients. *Journal of Clinical Medicine*, *12*(1), 45.

28. Wu, D., An, J., Yu, P., Lin, H., Ma, L., Duan, H., & Deng, N. (2021). Patterns for patient engagement with the hypertension management and effects of electronic health care provider follow-up on these patterns: cluster analysis. *Journal of Medical Internet Research*, *23*(9), e25630.
29. Curtis, L. H., Sola-Morales, O., Heidt, J., Saunders-Hastings, P., Walsh, L., Casso, D., ... & Quek, R. G. (2023). Regulatory and HTA Considerations for Development of Real-World Data Derived External Controls. *Clinical Pharmacology & Therapeutics*, *114*(2), 303-315.
30. Husby, A., Pottegård, A., & Hviid, A. (2021). Association between inhaled corticosteroid use and COVID-19 outcomes. *Pharmacoepidemiology and Drug Safety*, *30*(11), 1486-1492.
31. Massey, H., Gorczynski, P., Harper, C. M., Sansom, L., McEwan, K., Yankouskaya, A., & Denton, H. (2022). Perceived impact of outdoor swimming on health: a web-based survey. *Interactive Journal of Medical Research*, *11*(1), e25589.
32. Nasir, S., Khan, R. A., & Bai, S. (2024). Ethical framework for harnessing the power of AI in healthcare and beyond. *IEEE Access*, *12*, 31014-31035.
33. Vishwakarma, L. P., Singh, R. K., Mishra, R., & Kumari, A. (2023). Application of artificial intelligence for resilient and sustainable healthcare system: Systematic literature review and future research directions. *International Journal of Production Research*, 1-23.
34. Kumar, A., & Kumar, L. (2024). Navigating the Future: The Ethical, Societal and Technological Implications of Artificial Intelligence. *Journal homepage: https://gjrpublication. com/gjrecs*, *4*(02).