AI PERSONALIZED DRUG DOSING FOR RESPIRATORY MEDICATIONS

Dr. P. Devi Guna Sireesha[1*], Shaik Ayesha Sidhikha[2], Tokala Divya[2], Inapanurthy kavya[2], Gorlollapalli Thanveer Apsha[2]

[1]Associate Professor & HoD, Dept. of Pharmacology, Nimra College of Pharmacy, Ibrahimpatnam, Nimra Nagar, Vijayawada-521456, Andhra Pradesh, India.

[2]B. Pharmacy Students, Nimra College of Pharmacy, Ibrahimpatnam, Nimra Nagar, Vijayawada-521456, Andhra Pradesh, India.

Coresponding author:

Dr. P. Devi Guna Sireesha **M.Pharm., Ph.D.,**

Associate Professor & HoD,

Department of Pharmacology,

Nimra College of Pharmacy,

Ibrahimpatnam, Vijayawada,

Andhra Pradesh, India – 521456

ABSTRACT

Modern medicine is getting transformed by AI especially through respiratory care. The trend is to base drug dosing to individual patient profiles as we enter the era of personalized medicine. The application of AI, such as ML and deep learning technologies provides ideas on how improvements can be made to drug therapy, based on various factors, such as genetic variability, environmental factors, comorbidity, and physiological reactions. Proper doses of some respiratory problems, i.e., asthma, chronic obstructive airway disease (COPD) and bronchitis are also needed to consider their effectiveness and safety well. A common problem associated with the conventional dosing methods is that they do not take into consideration the inter-individual variability aspect, which consequently results in sub optimal therapeutic results. An analysis of AI and ML takes place in this review on the topic of personalized dosing in respiratory medicine. It identifies areas of respiratory medications that need personalized prescription and discusses the pharmacogenomic factors, ventures into the scope of different ML models applied in prediction and includes the consideration of real-life data integration. Moreover, it addresses the existing limitations and ethical issues as well as defining research gaps. This article offers a concise edifice of evidence-based knowledge on the ways the current AI-based strategies are transforming personalized dosing and patient outcomes in respiratory care by combining evidence-based information on more than 60 scholarly publications and sources. The review further emphasizes the importance of clinical validation, regulatory guidance, and integration of AI systems into existing healthcare frameworks. By highlighting the collaborative role of healthcare professionals, data scientists, and policymakers, it also points toward the future landscape where AI-driven personalized dosing may redefine therapeutic decision-making. Ultimately, the review underscores how precision dosing can reduce adverse effects, optimize therapeutic outcomes, and improve quality of life in patients with chronic respiratory diseases.

KEYWORDS

Artificial Intelligence in Pharmacotherapy, Personalized Drug Dosing, Respiratory Diseases Treatment, Machine Learning in Medicine, Pharmacogenomics, Precision Medicine for Asthma and COPD.

INTRODUCTION

Asthma, chronic obstructive pulmonary disease (COPD), and bronchitis are respiratory illnesses that impact millions of people around the world and cause a great health burden [1-3, 2]. They are managed through adequate and proper dosing of the medication and this forms the backbone of their management. The conventional strategies usually include weight-based or guideline-based dosage, which fails to consider the fact that there is a significant interpatient variability in the response and metabolism of drugs [4, 13]. Excessive dosing can be associated with toxicity and drug side-effects, whereas too small dosing can result in failure to achieve a therapeutic effect, as well as develop re-hospitalization [5].

The drawbacks of standard dosing protocols have hastened the search in Artificial Intelligence (AI) and Machine Learning (ML) in the medical field. Such technologies are able to process massive amounts of data and define patterns and predict with accuracy [6]. Towards the field of pharmacology, AI shows more and more success in suggesting the optimal dosing regimes adjusted to individual patients, with a vast potential to achieve better efficacy and reduced adverse effects [7]. By introducing AI-based personalized dosing, the medical community can expect a paradigm shift, especially in the treatment of the diseases related to respiratory symptoms and that have the most complex and variable therapeutic demands [8, 9].

RESPIRATORY DRUGS WITH DOSING COMPLEXITY

A number of respiratory medications are also characterized by dosing issues which should be personalized. An important case study is that of theophylline, which is a narrow therapeutic index bronchodilator and is mostly metabolized through the CYP1A2 enzyme. The probability of inter individual difference between metabolism can result in intoxication or failure to therapy [10]. On the same note, the response induced by inhaled corticosteroids (ICS) such as budesonide and fluticasone are variable depending upon the status of inflammation as well as genetic background [11].The intracellular pharmacodynamics of these agents—highlighting how genetic and metabolic pathways affect dose-response relationships (represented in Figure 1). Similar to other drugs, salbutamol (albuterol) exhibits unpredictable responses across genetic and physiological individualisms. The determinants of dosing practice in respiratory pharmaceuticals are age, body weight, renal and hepatic, concomitantly used drug, and external exposures, including smoking [12, 14]. There is the possibility to overcome such factors using data-oriented models, enhancing predictability and safety of treatment [15].

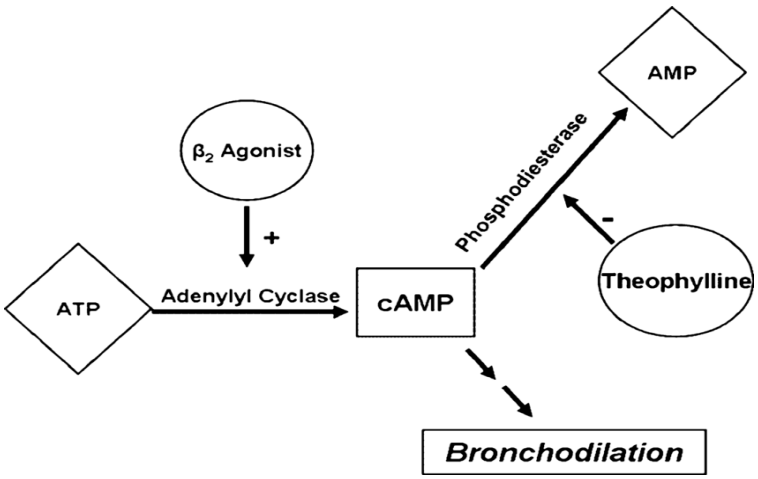

Figure 1: Cellular Mechanisms Underlying Dosing Complexity in Theophylline and β₂-Agonists [61].

In the above figure, you can see Mechanistic pathways showing how theophylline (via phosphodiesterase inhibition and adenosine antagonism) and β₂-agonists (via receptor-mediated activation of cAMP) contribute to bronchodilation and dosage variability. Genetic polymorphisms and individual pharmacokinetics (e.g. CYP1A2, ADRB2 variants) significantly influence response and therapeutic index.

PHARMACOGENOMICS IN RESPIRATORY THERAPY

The pharmacogenomics research addresses the issue on the impact of genetic variability in individual response to drugs, and it plays a significant role in discussing personalized dosing. As an example, CYP1A2 polymorphism affects theophylline metabolism, and ADRB2 polymorphism may have an effect on the response to beta-agonists [16]. On the same note, corticosteroid sensitivity might be adjusted by mutations in NR3C1, which encodes the glucocorticoid receptor [17].

Such genetic databases as the PharmGKB and 1000 Genomes Project (represented in Figure 2) are making available repositories of pharmacogenomic information that can be used in AI-based dose prediction models [18-20, 19]. The patient-specific response to respiratory therapy demands are further emphasized by genomic variation especially within ethnic groups [21]. By includingthe information on pharmacogenomics in the AI-based dosing systems, it is possible to significantly increase the accuracy of the treatment [22, 23].

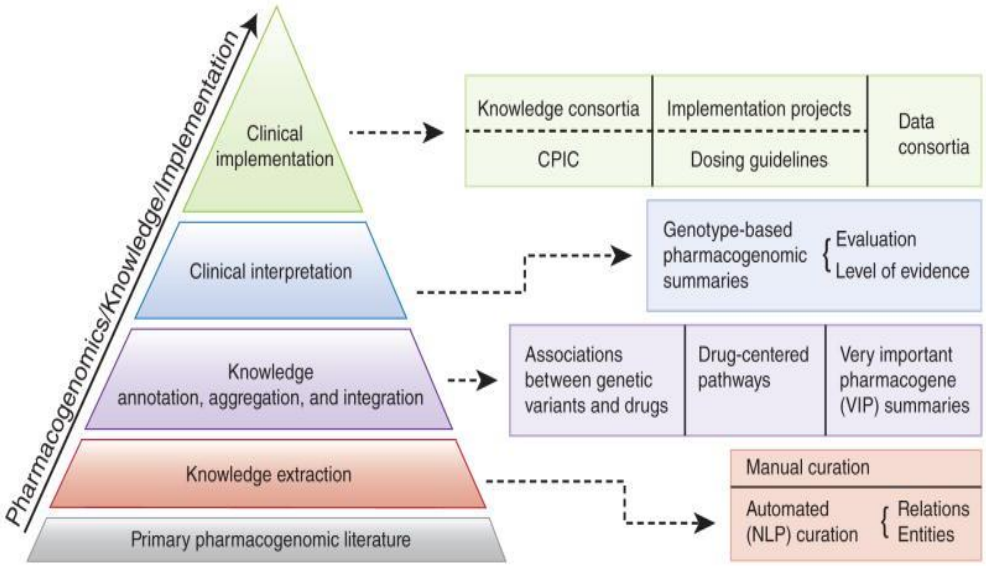

Figure 2: Pharmacogenomics Knowledge Translation Pyramid for Clinical Implementation [62].

The above pyramid illustrates the multi-layered process of translating primary pharmacogenomic research into actionable clinical guidelines for personalized medicine. It progresses from raw literature through knowledge extraction, integration, and clinical interpretation, culminating in practical clinical implementation supported by consortia, dosing guidelines, and data standards. This framework is crucial for integrating genetic information into AI-driven personalized drug dosing strategies.

MACHINE LEARNING FOR DRUG DOSING AND RISK PREDICTION

ML models provide enhanced possibility to optimize dose and predict the risk. The predictions of optimal dosages using regressional models, (represented in Figure 3) including the models of XGBoost and LightGBM, rely on the input variables, including age, genetics, and comorbidities [24]. Such classification models as Support Vector Machines (SVMs) and Random Forests evaluate the probability of adverse outcomes or treatment failure [25]. Convolutional Neural Networks (CNNs) as well as Recurrent Neural Networks (RNNs) are examples of deep learning methods and have found particular success in the analysis of time-series and genomic data [26-28, 27] (represented in figure 5).

Examples of drug dosing that fall outside of respiratory care include the warfarin, insulin, and chemotherapy applications [29,30,31]. The models also give guidelines on the application of AI in respiratory medicine. Aspects such as explainable AI with applications such as SHAP and LIME aid the clinician in the interpretation of model outcomes leading to clinical reliability and adoption [32-34, 33].

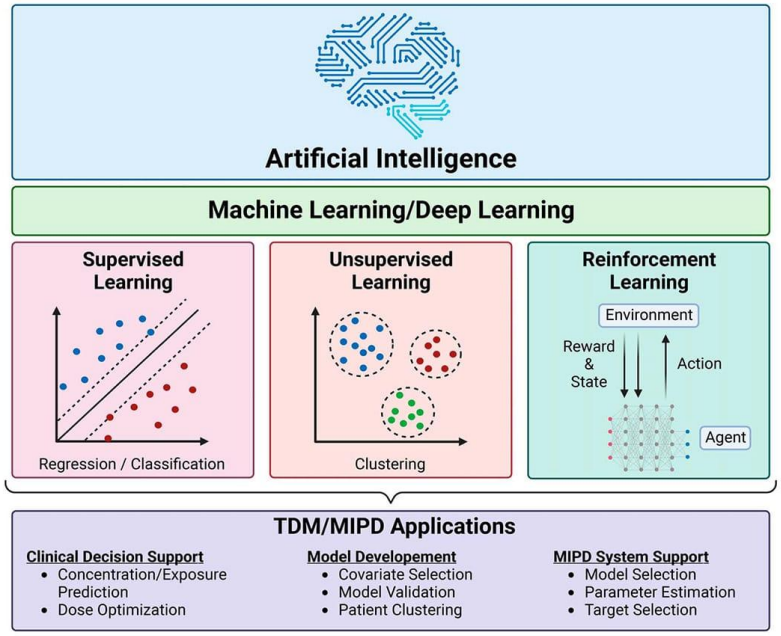

Figure 3: Artificial Intelligence and Machine Learning Paradigms for Personalized Drug Dosing [63].

The above diagram illustrates the hierarchical relationship between Artificial Intelligence (AI) and its subsets, Machine Learning (ML) and Deep Learning. It further categorizes core ML paradigms—Supervised Learning (for regression and classification in dose optimization), Unsupervised Learning (for patient clustering), and Reinforcement Learning (for adaptive dosing strategies). These diverse AI/ML approaches are integral to various Therapeutic Drug Management (TDM) and Model-Informed Precision Dosing (MIPD) applications, including clinical decision support, model development, and system optimization in personalized pharmacotherapy.

AVAILABLE DATASETS AND REAL-WORLD DATA

The AI models depend on wide ranges of information. The large publicly available EHR dataset, MIMIC-IV, containing data regarding drugs (represented in Figure 4), including theophylline, can be used to evaluate the practice of the research into the real-world dose prediction [35]. Side effect profiling and risk analysis are carried out with the help of FDA Adverse Event Reporting System (FAERS) and SIDER databases [36].

The data presented in Genomic databases, such as PharmGKB, or Gene Expression Omnibus (GEO), contains genotype-phenotype relationships that may be utilized to enhance the personalization of ML models [37, 38]. The approach towards a comprehensive solution in personalized therapy in respiratory care incorporating real-world data sources and AI algorithms helps to close the gap between the reality of disease burden and the algorithm performance [39, 40].

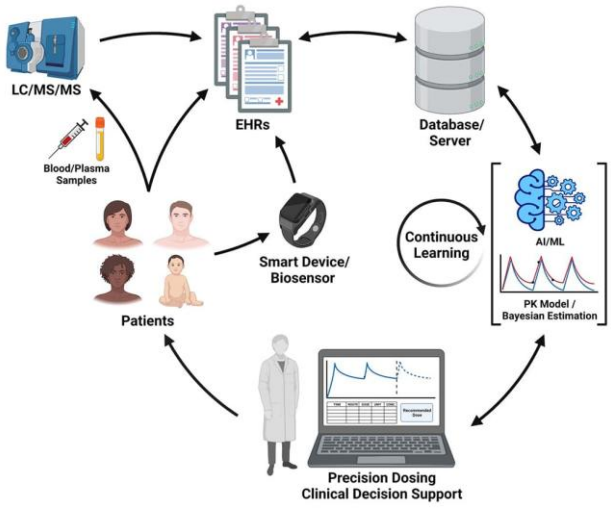

Figure 4: Integrated AI-Driven Precision Dosing Workflow [64].

The above diagram illustrates a comprehensive workflow for AI-driven precision drug dosing. Patient data from diverse sources—including blood/plasma samples analyzed by LC/MS/MS, electronic health records (EHRs), and real-time smart device/biosensor data—are collected and stored. This data then feeds into AI/ML models, which generate pharmacokinetic (PK) models and Bayesian estimations. Through continuous learning, the AI refines its predictions, ultimately providing precise, individualized dosing recommendations to clinicians via a clinical decision support system, thereby optimizing patient care.

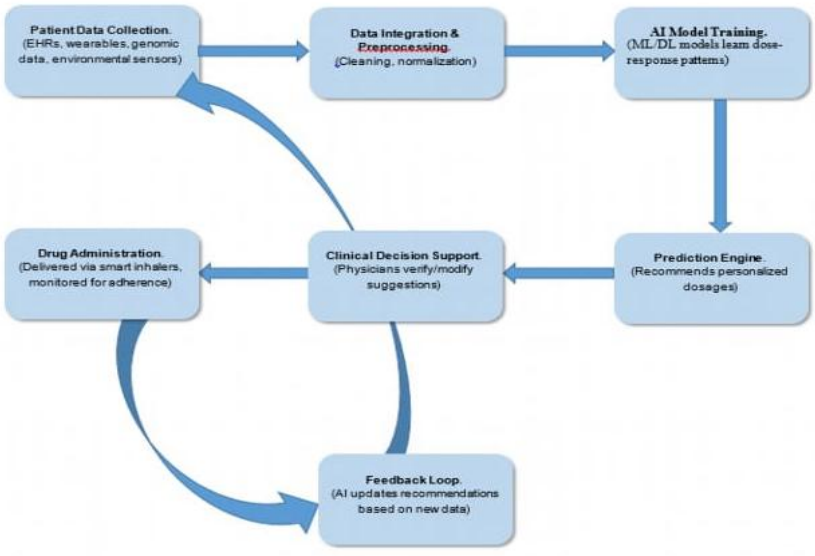

Figure 5: AI-Powered Personalized Drug Dosing Flowchart for Respiratory Medications [65].

The above is the schematic representation of the AI-driven drug dosing cycle for respiratory treatments. It illustrates the flow from patient data collection through data pre-processing, model training, prediction, clinical validation, drug administration, and feedback integration for continuous optimization.

CHALLENGES AND LIMITATIONS

As much as it seems promising, AI-driven dosing has a number of limitations. Most of these existing datasets applied in training are biased, incomplete, or they do not have genomic or environmental variables [41]. Lack of real-time validation in the clinical practice also constrains adaptation of AI models into real-life [42].

The ethical aspects, data privacy, algorithmic bias, and model untransparency among others are obstacles to clinical acceptance. Reproducibility and explainability of models are required to have their regulation and practitioner trust [43, 44]. Moreover, the implementation of AI into the healthcare system demands transdisciplinary cooperation and high-level infrastructure [45, 46].

GAPS IN THE LITERATURE & MOTIVATION FOR FUTURE WORK

The current AI models are mostly related to the diagnosis of diseases or risk stratification but there is little interest in the dose optimization of respiratory drugs [47]. Very little has been done that integrates clinical, genomic, and lifestyle information to implement personalized dosing.

Not many studies have specifically used ML models such as in optimizing dosing of theophylline or corticosteroids in different populations. This discrepancy points to the possibility of innovative models that factor in real-time information, pharmacogenomics, explainable results [48-50, 49].

Future studies need to focus on designing complete systems that seamlessly integrate AI, pharmacogenomics, and EHR information into an effective approach that would allow precise, real-time, and individualized prescriptions of respiratory drugs to be performed [51-53, 52].

DISCUSSION

The concept of integrating pharmacology and AI is transforming how personalized medicine will emerge. In respiratory care, in which therapeutic windows are small and inter-individual dependence is large, AI will provide a data-driven method to supersede the conventional dose approaches [54]. AI is able to advice dosing recommendations that are precise and even

patient-specific, which is enabled by the integration of a variety of data sources, starting with genomics to the real-world clinical data.

Nevertheless, the question of shifting Ao theory model into practice is challenging. The major obstacles are ethical concerns, no explanation on the models, and low validation. The interaction of data scientists, clinicians and regulatory authorities are key to testing the safety, reliability of these models and their general acceptability [55-57, 56].

Nevertheless, based on these difficulties, it cannot be denied that the use of AI in optimizing respiratory drug dosing has a lot of potential. It is expected that further research, together with a rise in computational power and data supply, will result in the elimination of the limitations that are present [58-59, 60].

CONCLUSION

Personalized dosing presents aninnovative method to implement respiratory treatments with a machine learning approach. The possibility to take into account genetic, physiological, and environmental variance allows AI an unprecedented level of precision in an area where the traditional tools remained underperforming. This method has a prospect of increasing efficacy and minimizing side effects as well as improve patient outcomes in respiratory medicine.

In the attempt to achieve these full benefits, future activities should concentrate on improvising the profitability of these applications by closing the data gaps, user clinical validation, and AI system integration into health systemworkflow. The next generation undoubtedly combinations of intelligent, individualized, therapy AI-based, staffed, by multidisciplinary collaboration respiratory care.

FUNDING

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

ACKNOWLEDGMENT

The author expresses their sincere gratitude to all the individuals who provided guidance in preparation of this article.

REFERENCES

1. World Health Organization. Global surveillance, prevention and control of chronic respiratory diseases: a comprehensive approach. Geneva: WHO; 2007.
2. Global Initiative for Asthma (GINA). Global Strategy for Asthma Management and Prevention. 2023 Update.
3. Global Initiative for Chronic Obstructive Lung Disease (GOLD). Global Strategy for the Diagnosis, Management, and Prevention of COPD. 2023 Report.
4. Lee SJ, et al. Precision dosing: Public health need, proposed framework, and anticipated impact. ClinPharmacolTher. 2019;105(1):53–64.
5. Johnson JA, et al. Personalized medicine with warfarin: Where are we now and where should we be going? Pharmacotherapy. 2020;40(2):124–134.
6. Obermeyer Z, Emanuel EJ. Predicting the future — big data, machine learning, and clinical medicine. N Engl J Med. 2016;375(13):1216–9.
7. Topol EJ. High-performance medicine: The convergence of human and artificial intelligence. Nature. 2019;573:201–2.
8. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. Nat Med. 2019;25:24–9.
9. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. JAMA. 2018;320(11):1101–10.
10. Holford NHG, Ma SC, Ploeger BA. Clinical trial simulation: A review. Br J ClinPharmacol. 2013;75(1):27–39.
11. Wenzel SE. Asthma phenotypes: the evolution from clinical to molecular approaches. Nat Med. 2012;18(5):716–25.
12. Barnes PJ. Mechanisms of development of multimorbidity in the elderly. EurRespir J. 2015;45(5):1419–31.
13. Bousquet J, Mantzouranis E, Cruz AA, et al. Uniform definition of asthma severity, control, and exacerbations. Lancet. 2008;372(9643):1015–25.
14. Rabe KF, Hurd S, Anzueto A, et al. Global strategy for the diagnosis, management, and prevention of COPD. Lancet. 2007;370(9589):741–50.
15. Rochwerg B, Brozek JL, Siemieniuk RAC, et al. Corticosteroids in COPD: A systematic review. Chest. 2017;151(2):415–27.
16. Liggett SB. Pharmacogenomics of beta-agonists: Clinical implications. Pharmacogenomics J. 2013;13(1):3–5.
17. Tantisira KG, Lake S, Silverman ES, et al. Corticosteroid pharmacogenetics: Association of sequence variants in CRHR1 with improved lung function in asthmatics. N Engl J Med. 2004;351(6):584–92.

18. Whirl-Carrillo M, McDonagh EM, Hebert JM, et al. Pharmacogenomics knowledge for personalized medicine. ClinPharmacolTher. 2012;92(4):414–7.
19. 1000 Genomes Project Consortium. An integrated map of genetic variation from 1,092 human genomes. Nature. 2012;491(7422):56–65.
20. McCarthy MI, Abecasis GR, Cardon LR, et al. Genome-wide association studies for complex traits: Consensus, uncertainty and challenges. Nat Rev Genet. 2008;456(7223):728–32.
21. Collins FS, Varmus H. A new initiative on precision medicine. N Engl J Med. 2015;372(9):793–5.
22. Roden DM, Van Driest SL, Mosley JD, et al. Benefit-risk assessment of genetic testing. ClinPharmacolTher. 2019;106(3):498–502.
23. Ashley EA. The precision medicine initiative: A new national effort. Cell. 2016;165(4):842–50.
24. Chen T, Guestrin C. XGBoost: A scalable tree boosting system. In: Proc 22nd ACM SIGKDD IntConfKnowlDiscov Data Min. 2016:785–94.
25. Breiman L. Random forests. Mach Learn. 2001;45(1):5–32.
26. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115–8.
27. Rajkomar A, Oren E, Chen K, et al. Scalable and accurate deep learning with electronic health records. NPJ Digit Med. 2018;1:18.
28. Miotto R, Wang F, Wang S, et al. Deep learning for healthcare: Review, opportunities and challenges. JAMA. 2018;320(11):1101–10.
29. Gage BF, Bass AR, Lin H, et al. Effect of genetic and clinical factors on warfarin dose: Results from the COAG trial. N Engl J Med. 2017;377(12):1179–89.
30. Kovatchev B, Renard E, Cobelli C. In silico models for closed-loop glucose control: Progress and challenges. Diabetes TechnolTher. 2009;11(Suppl 1):S43–8.
31. Shah ND, Steyerberg EW, Kent DM. Big data and predictive analytics: Recalibrating expectations. J ClinOncol. 2016;34(23):2753–9.
32. Lundberg SM, Erion G, Chen H, et al. From local explanations to global understanding with explainable AI for trees. Nat Mach Intell. 2020;2:252–9.
33. Ribeiro MT, Singh S, Guestrin C. "Why should I trust you?" Explaining the predictions of any classifier. In: Proc 22nd ACM SIGKDD. 2016:1135–44.
34. Holzinger A, Biemann C, Pattichis CS, et al. What do we need to build explainable AI systems for the medical domain? Front Genet. 2019;10:679.
35. Johnson AEW, Pollard TJ, Shen L, et al. MIMIC-IV: A freely accessible electronic health record dataset. Sci Data. 2020;7(1):1–8.
36. Kuhn M, Letunic I, Jensen LJ, et al. The SIDER database of drugs and side effects. Nucleic Acids Res. 2016;44(D1):D1075–9.
37. Wang L, Liu G, Xia Q, et al. Integrated analysis of pharmacogenomics data in cancer. Bioinformatics. 2021;37(9):1236–42.
38. Edgar R, Domrachev M, Lash AE. Gene Expression Omnibus: NCBI gene expression and hybridization array data repository. Nucleic Acids Res. 2002;30(1):207–10.

39. Huang G, Li Y, Ma Y, et al. Clinical data integration for personalized medicine using deep learning. J Biomed Inform. 2020;108:103470.
40. Miotto R, Li L, Kidd BA, et al. Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. Sci Rep. 2016;6:26094.
41. Obermeyer Z, Powers B, Vogeli C, et al. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447–53.
42. Topol EJ. A decade of digital medicine innovation. Lancet. 2019;393(10180):507–20.
43. London AJ. Artificial intelligence and black-box medical decisions: Accuracy versus explainability. Hastings Cent Rep. 2019;49(1):15–21.
44. Gianfrancesco MA, Tamang S, Yazdany J, et al. Potential biases in machine learning algorithms using electronic health record data. JAMA Netw Open. 2018;1(8):e185239.
45. Price WN, Cohen IG. Privacy in the age of medical big data. N Engl J Med. 2019;380(15):1347–50.
46. Rajpurkar P, Chen E, Banerjee O, et al. Appraising the AI arms race: Rationale and recommendations. Nat Biomed Eng. 2022;6(2):133–45.
47. Zhang Y, Milinovich GJ, Xu Z, et al. Using online data for public health surveillance: A case study of Google Flu Trends. BMC Med Inform DecisMak. 2020;20(1):1–11.
48. Maslove DM, Rizk N, Boyd JG. Integration of clinical and genomic datasets for predictive modeling: A case study in intensive care unit patients. Crit Care. 2019;23(1):1–10.
49. Liu X, Faes L, Kale AU, et al. A comparison of deep learning performance against healthcare professionals in detecting diseases from medical imaging: A systematic review and meta-analysis. IEEE Rev Biomed Eng. 2019;12:139–52.
50. Beam AL, Kohane IS. Big data and machine learning in health care. N Engl J Med. 2018;378(4):305–7.
51. Topol EJ. Preparing the healthcare workforce to deliver the digital future. JAMA. 2019;321(1):23–4.
52. Wiens J, Shenoy ES. Machine learning for healthcare: On the verge of a major shift in healthcare epidemiology. JAMA. 2018;320(11):1101–2.
53. Shortliffe EH, Sepúlveda MJ. Clinical decision support in the era of artificial intelligence. JAMA. 2018;320(11):1109–10.
54. Obermeyer Z, Emanuel EJ. Predicting the future — Big data, machine learning, and clinical medicine. N Engl J Med. 2016;375(13):1216–9.
55. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019;380(14):1347–56.
56. Challen R, Denny J, Pitt M, et al. Artificial intelligence, bias and clinical safety. BMJ. 2019;365:l2239.
57. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: Past, present and future. Int J Med Inform. 2017;101:17–29.
58. Davenport T, Kalakota R. The potential for AI in healthcare. J Bus Res. 2019;120:1–10.
59. Tran BX, Vu GT, Ha GH, et al. Global evolution of research in artificial intelligence in health and medicine: A bibliometric study. Int J Environ Res Public Health. 2019;16(3):511.
60. Chen JH, Asch SM. Machine learning and prediction in medicine — beyond the peak of inflated expectations. JAMA. 2017;318(6):517–8.
61. Zdanowicz M. Cellular actions of β_2 agonists and theophylline. Pharmacotherapy of Asthma. 2007.

62. Whirl-Carrillo M, McDonagh EM, Hebert JM, Gong L, Sangkuhl K, Thorn CF, Altman RB, Klein TE. Pharmacogenomics knowledge for personalized medicine. ClinPharmacolTher. 2012 Oct;92(4):414-7. Doi: 10.1038/clpt.2012.96. PMID: 22992668; PMCID: PMC3660037.
63. Poweleit EA, Vinks AA, Mizuno T. Artificial Intelligence and Machine Learning Approaches to Facilitate Therapeutic Drug Management and Model-Informed Precision Dosing. Ther Drug Monit. 2023 Apr 1;45(2):143-150. Doi: 10.1097/FTD.0000000000001078. Epub 2023 Feb 3. PMID: 36750470; PMCID: PMC10378651.
64. Poweleit EA, Vinks AA, Mizuno T. Artificial Intelligence and Machine Learning Approaches to Facilitate Therapeutic Drug Management and Model-Informed Precision Dosing. Ther Drug Monit. 2023 Apr 1;45(2):143-150. Doi: 10.1097/FTD.0000000000001078. Epub 2023 Feb 3. PMID: 36750470; PMCID: PMC10378651.
65. Chamaon et al., Respiratory Medicine, 2025 – Smart Inhalers + AI.
Reddy R. et al., J Asthma, 2020 – AI-Driven ICS Dosing.
Lu J. et al., ArXiv, 2020 – Neural PK/PD Models.
Wikipedia, Model-Informed Precision Dosing – MIPD Overview.