

ROLE OF ARTIFICIAL INTELLIGENCE IN PERSONALIZED MEDICINE A
COMPREHENSIVE REVIEWChittesh K. A.¹, Thibiraj C.¹, Jeyaprabha P.^{1*}, Sambath Kumar R.¹¹Department of Pharmaceutics, The Erode college of Pharmacy, Veppampalayam, Erode- 638 112, Tamilnadu, India,
Affiliated to the Tamilnadu Dr. M. G. R Medical University, Chennai, India.***Corresponding Author: Jeyaprabha P.**Associate Professor, Department of Pharmaceutics, The Erode College of Pharmacy, Veppampalayam, Erode-
638 112, Tamilnadu, India, Affiliated to the Tamilnadu Dr. M. G. R Medical University, Chennai, India.DOI: <https://doi.org/10.5281/zenodo.23032010>**How to cite this Article:** Chittesh K. A.¹, Thibiraj C.¹, Jeyaprabha P.^{1*}, Sambath Kumar R.¹ (2026). Role Of Artificial
Intelligence In Personalized Medicine A Comprehensive Review. European Journal of Pharmaceutical and Medical Research,
13(10), 142–150.This work is licensed under [Creative Commons Attribution 4.0 International license](https://creativecommons.org/licenses/by/4.0/).

Article Received on 02/09/2026

Article Revised on 23/09/2026

Article Published on 01/10/2026

ABSTRACT

The idea behind personalized medicine is simple to explain but difficult to execute: prevention, diagnosis, prognosis and treatment should be based on the biological, clinical, environmental and behavioral specificities of the patient who is in front of the clinician, rather than the average patient of a trial population. In fact, one of the key technologies driving this goal is artificial intelligence (AI), which can manage data that is often too big, too complex, or too multidimensional to be comfortably handled by traditional statistical methods. Nevertheless, AI has not fully matured and is still experiencing its adolescence in the field of personalized medicine in the domains of biomarker discovery, disease subtyping, risk prediction, early diagnosis, treatment-response modelling, pharmacogenomics, digital pathology, longitudinal monitoring, and clinical decision support. It outlines the conceptual foundations, types of data that enable personalization, key clinical applications, ethical and legal issues yet to be resolved, and obstacles between potential research and clinical practice. The perpetual debate is that AI does not take over the doctor's decision-making, but rather helps doctors to access more information than they could retain within their minds all at once.

KEYWORDS: Personalized medicine; Precision medicine; Artificial intelligence (AI); Machine learning; Clinical decision support.**1. INTRODUCTION**

Realizing that two patients with the same diagnosis will behave differently, if they feel it is a valid observation, is the starting point of the case for personalized medicine. They vary in nature of the disease, prognosis, and response to a specific therapy. To date, medicine has addressed this diversity through reliance on population averages, guideline pathways, and categories of diagnosis that are broad for a reason. What is important is that these tools were never designed to deal with the more specific question — for which patient, at which moment and with which intervention — and that is the question personalized medicine is seeking to answer. This involves gathering molecular, physiological, imaging, environmental and behavioral data and then integrating them into decisions for an individual rather than a population.^[1,5,6,11] The real challenge is scale and

the fact that it is quite heterogeneous. The modern health system produces genomic sequences, transcriptomic and proteomic profiles, radiology images, digital pathology slides, laboratory results that span months or years, medication histories, and free text clinical notes – and more and more, continuous streams from wearable devices. Even the most experienced clinician cannot retain all of that in his or her working memory and apply it in a consistent way to all patient cases. This is the space AI has come into. AI has emerged as a key tool in the personalisation project, not merely as a shortcut to automation, but as a tool that interprets the mammoth volume of patient data presented as a clinician can use it.^[1,3,5,6,12] While the applications of AI continue to grow, from personalized risk estimation and disease classification to the discovery of biomarkers, drug selection, and optimization of treatment, remote

monitoring, and even the creation of synthetic datasets for the further development of models, most of the literature mentioned above is careful to point out that clinical translation is only partially achieved.^[5,7,8] This review aims to be a truthful reflection of the state of the art in AI for personalized medicine — what it can achieve, where its limitations are, and what it would require to be done responsibly.^[6,8-10]

2. CONCEPTUAL BASIS OF AI IN PERSONALIZED MEDICINE

The premise underlying personalized medicine is quite straightforward: clinically similar patients may well be biologically very different in ways that have therapeutic significance. The role of AI in such an environment is self-evident because, unlike conventional approaches to science and technology, AI does not require a complete prior specification of which variables are relevant before it can do any learning. Supervised learning applications usually revolve around diagnosis, prognosis, and treatment prediction, whereas unsupervised learning applications tend to focus on clustering, subtyping, and representation learning. Deep learning has been particularly valuable in imaging and pathology, where it has the capacity to directly learn from unstructured raw pixel data instead of being restricted to engineered features. NLP takes this a step further by extracting patient-specific information from free-text clinical records and the biomedical literature.^[1,3-6]

One of the most impactful changes in the field of AI has been the transition from single modality systems to multimodality AI. Decisions in the clinic are never made using a single biomarker or a single image in isolation but are the result of the convergence of multiple elements — symptoms, laboratory results, imaging, past history of medication, genetic makeup, social environment, and the development of the disease process over time. A multimodal AI system tries to integrate the multiple and disparate elements of information into a single coherent representation of the patient, which represents a departure from previous models of decision-making based on the one-to-one mapping between biomarker and decision.^[5,6,12]

The second important concept to highlight here is that of temporality. Personalized medicine cannot be a one-time event conducted at baseline but must be a continuous and evolving process in response to changing biology, symptomatology, exposures and effects of treatment. This has been incorporated in the current generation of AI-based systems as risk scores, diagnoses, and treatment recommendations are continuously updated using the incoming longitudinal data.^[5,6,11] This is the reason why AI has found a ready application in the realm of chronic diseases, cancer surveillance and remote monitoring where a once-and-done approach is inadequate.

3. CORE DATA MODALITIES ENABLING PERSONALIZED AI

Genomics continues to play an integral role in personalized medicine because it is the inherited and somatic mutations that affect disease predisposition, metabolism of drugs, and responsiveness to treatments in unique ways depending on each individual patient. Models developed using big datasets of genomics data and their correlation to patient outcomes enable identification of molecular phenotypes, identification of actionable mutations, and risk stratification with much more accuracy compared to the traditional one-gene approach.^[1,2,5,11] The advancement of cheaper and more accessible sequencing technologies allowed for the creation of space for personalized risk assessment and treatment strategy selection, especially in oncology and rare diseases.

Proteomics, metabolomics, and transcriptomics provide information that genetic code alone does not — the snapshot of what is actually taking place biologically at this particular point in time. These types of data are generally characterized by high dimensionality and noise levels and that is precisely the type of situation where traditional statistical approaches fail and AI models work better. Using signals from multiple layers of omics, AI algorithms are able to generate complex signatures that will differentiate between disease phenotypes and allow for more accurate outcome predictions.^[5,12]

Imaging and pathology provide another type of information — detailed phenotype through high resolution imaging that complements molecular profiling data.^[46,47] Deep learning algorithms have demonstrated impressive results in radiology, histopathology, ophthalmology, dermatology and cardiology through identifying subtle image patterns correlated with disease severity, prognosis, and response to therapy.^[1,5,6] As imaging does not require invasive procedures, it provides an excellent opportunity for stratifying patients. In addition, digital pathology takes imaging one step forward by providing spatial and microenvironment context, which has become crucial in such fields as cancer immunotherapy and resistance to treatment.^[13]

Finally, EHRs, laboratory data, pharmacy data, clinical notes, and wearable devices constitute longitudinal spine of the data that needs interpretation with molecular and imaging data. NLP allows turning narrative text into structured data, and models based on EHR and monitoring data allow recognizing early patterns of deterioration, intolerance to therapy or lack of response to treatment.^[1,5,6] All this data combined allows building evolving patient-specific models.

4. AI FOR RISK PREDICTION AND PREVENTIVE PERSONALIZATION

Prediction of risk is likely one of the most mature fields of clinical use of AI for personalized medicine at the moment. Traditional risk predictors are based on a few

predictors and give the average risk prediction for the large group of people. AI can go beyond that and take into account the complicated interplay of genetic, clinical, imaging, and behavioral factors to predict the risk of disease development, progression, recurrence, or complications related to the treatment in case of an individual patient, rather than some subpopulation.^[1,5,6,11] In theory, it allows for more tailored preventive care and screening intervals according to risks and better resource allocation in healthcare.

In cardiovascular medicine, models taking into account the combination of ECG characteristics, imaging data, biomarkers, and EHRs are applied for the prediction of increased risk of heart failure, arrhythmia, or any other cardiovascular problem.^[5,6,34,35,36] The same is true for oncology, as it concerns the estimation of the risk of recurrence, metastasis, or the risk of the side effects caused by systematic treatment.^[13] AI in diabetes or kidney diseases can be used for predicting the risks of progression and identifying patients who require careful monitoring or changes in treatment.^[5,12,40]

One of the benefits associated with preventive personalization is the fact that people who do not require such tests will be able to avoid undergoing them. However, for this to happen, the models have to be accurate and their predictions should help to improve the outcome of the process. There is a possibility that an inaccurate model will result in a feeling of anxiety or even waste of the available resources.^[10] The fact is that risk-prediction models should be integrated into some kind of workflow that will provide a solution to the problem.

5. EARLY DIAGNOSIS AND REFINED DISEASE CLASSIFICATION

However, the benefits of AI in diagnosis go beyond just speed; the ability to detect the presence of disease early is important in itself due to improved outcomes in the presence of timely treatment. However, in personalized medicine, the objective is to categorize diseases based on biological features that may warrant a completely different course of action. AI technology is uniquely positioned to perform such tasks since it can discern fine detail from imaging, pathology, genomics, electrophysiology, and clinical data that can easily escape routine assessment.^[1,5,6]

In cancer medicine, AI technology was applied for tumor classification by its molecular subtype, pathologic architecture, immune microenvironment, and prediction of response to treatment.^[5,13] Neurodegenerative disorders have overlapping presentations, and AI technology can help separate them by using images in conjunction with changes in clinical presentation in the longitudinal studies.^[39] In infectious and inflammatory disorders, AI can identify subgroups with different mechanisms of the underlying processes hidden behind one diagnostic term, paving the way to targeted

therapeutic interventions.^[5,12] The common factor in all these examples is that AI technology does not merely automate the current classification systems in some cases – it helps to redefine the taxonomy of diseases around new, clinically relevant categories.

Diagnosis also has a dynamic component to which artificial intelligence is suited. The incoming stream of data – through repeat images, lab changes, medication impacts, physiology from wearables – will be used to update probabilities, allowing for a more flexible approach to clinical thinking.^[5,6] This also aligns with the way personalized medicine approaches diagnosis: not a one-time label, but something to continually refine as information emerges.

6. BIOMARKER DISCOVERY AND DISEASE SUBTYPING

Biomarkers form the currency of precision medicine, because an indication of the underlying mechanisms of a disorder, of patient prognosis, or of potential treatment effects has to be quantifiable. The AI-based strength in biomarker discovery is the ability to mine vast amounts of data — molecular, imaging, and clinical — to find correlations in the context of survival, relapse, toxicities, and benefits, and to do so multivariable instead of single-factor.^[1,5,12]

This has been pioneered by cancer research, applying AI algorithms to data such as gene expression profiles, proteomics, radiomics, digital pathology images, and multi-omics integrated modeling to discover biomarkers.^[13] Since AI-assisted biomarkers based on ordinary clinical data can be developed more quickly and less expensively than comprehensive molecular characterization, this also makes precision care accessible even in those circumstances when deep sequencing is out of reach.^[14] Similar efforts exist in cardiology, neurodegeneration, autoimmunity, and psychiatry.^[5,6,12]

Disease subtyping is the logical progression from biomarker discovery, where many diseases which used to be considered one disease entity have now been discovered to consist of biologically different subtypes, and AI-based clustering has proved effective in discovering such hidden subtypes, with beneficial applications in trials and therapy decisions.^[5,6,11] The problem, however, is that biomarker discovery tools can suffer from overfitting and poor validation processes; therefore, prospective validation and biological plausibility are still critical steps before implementing an AI-generated biomarker.^[8,10]

7. TREATMENT SELECTION AND RESPONSE PREDICTION

Drug selection, probably, is one of the most evident examples of the application of AI in personalized medicine and has the greatest value in clinical practice. If there are multiple treatment choices for an individual, AI

algorithms could be used to assess the expected efficacy of different options, possible risks and, eventually, the best sequence of therapies. This goes beyond diagnostics and aims at personalizing the treatment process.^[1,5,6,12]

In oncology, AI algorithms utilize data on tumor genetics, tissue pathology, imaging, past experiences with drug treatment and clinical characteristics to predict patients' sensitivity to chemotherapy, targeted therapy, hormone therapy or immunotherapy.^[5,13,11] Existing biomarkers, including PD-L1 expression, tumor mutation load, and microsatellite instability have revealed inconsistent effectiveness in different types of tumors, and there are emerging studies indicating that multimodal AI signatures perform better than any particular marker in predicting patients' response.^[15,37] AI approaches are currently under investigation in psychiatry and neurology as a means of reducing the number of trials needed before selecting the right treatment regimen, predicting patients' response to antidepressants, neurostimulation therapy, antiepileptics, or disease-modifying drugs based on multimodal patient data.^[5,11,41,42,43]

AI can facilitate treatment modifications before failure is apparent by identifying nonresponse or signs of toxicity. Instead of waiting for treatment to fail, clinicians may act sooner using nonresponse signals. This is crucial as early correction is just as important as the original therapy choice in personalized medicine.^[5,6] In the case of chronic illness, AI models can utilize multiple data inputs (glucose levels, renal function, symptom scores, data from wearables, etc.) to help determine the optimal timing for follow-up appts and the appropriate level of treatment/modalities to employ.^[12]

8. PHARMACOGENOMICS AND DRUG DOSING

Pharmacogenomics may represent the most prominent intersection of AI and personalized medicine. Genetic polymorphisms are only the beginning in understanding drug metabolism and response. Genotype is only one piece of the puzzle in pharmacogenomics. The intricacies of pharmacogenomics lies in age, sex, renal and hepatic decline, comorbid conditions, polypharmacy, diet, and even medication adherence. AI's greatest strength lies in its capacity to analyze the complex interplay of a multitude of phenomena and create a prediction in the same sphere as a pharmacogenomics algorithm, only with much greater complexity.^[1,2,5]

There are many diverse applications in medicine, including but not limited to, anticoagulation, psychiatry, pain management, and even cancer management. AI in these domain addresses the prediction of dosing, toxicity, and even the creation of individualized monitoring plans for patients with high risk of adverse drug interactions and a complicated pharmacogenomic profile.^[5,12,33] These systems aim to predict the most accurate drug response by combining both the pharmacogenomics and

the clinical and population health data integrated with the laboratory.

Of all the customized medicine offerings, pharmacogenomics has perhaps the most developed of all the systems, though, in reality, has been implemented in very few of the world's health systems. AI has the potential to address the deficit in this area. However, for this to truly be the case, its recommendations must be validated and implemented in a clinical workflow system for the prescribers. This would be much more than a proof of concept.

9. IMAGING, RADIOMICS, AND DIGITAL PATHOLOGY

Medical imaging applies AI in a number of ways; however, in the field of personalized medicine, the utility of imaging transcends the speed and accuracy of detection. Imaging-derived AI captures and utilizes phenotypic signatures. These signatures assist in the identification of treatment responders and account for the inclusion of harmful spatial variance and irregularity in personalized medicine. In cancer studies, the fields of radiomics and pathomics have become dominant disciplines for the integration of imaging and its relation to molecular subtyping, immune analysis, and prognosis.^[5,13,15,23,24]

The field of radiogenomics is appealing to many because it provides a non-invasive technique for the categorization of patients using imaging techniques, where in many cases imaging features can determine a tumor's molecular subtype or relevant treatment characteristics without the need for a biopsy to be performed.^[5,13,48,49,50] Whole-slide pathology analysis of tissue imaging focuses on cellular composition and arrangements of tissue and can determine microenvironmental context which may assist in determining mutation status, prognosis, and treatment outcome.^[13,14]

The above concepts can also be used for many other imaging studies, beyond cancer. In cardiology, imaging can help to describe the remodeling of the heart and its impact on when it is best to intervene.^[34,35,36] In dermatology, the use of imaging techniques can be utilized for more fine-grained distinctions in diagnosis, as well as for the more frequent monitoring of patients. In the field of ophthalmology, imaging techniques can be employed for more refined distinctions of diagnosis and frequent monitoring of patients.^[21,22] To overcome the challenges currently being addressed, there must be no variations in imaging technique implementations, which is the biggest obstacle to the implementations.^[8,10]

10. EHRs, NLP, AND LONGITUDINAL CLINICAL DECISION SUPPORT

AI tools are made relevant to clinical workflows through EHRs because the problems associated with putting molecular information and imaging into a context for the

individual patient's history are specific. This is because, as mentioned, molecular and imaging findings need to be connected to the longitudinal information that EHRs house, to make AI applicable to clinical settings. Individualized decisions are based on diagnosis, treatment, lab trends, toxicities, admissions and outcomes. Models developed using EHRs can identify a risk of worsening, alert to potential treatment problems, adjust the level of follow-up, and facilitate chronic disease management more generally.^[1,5,6] This is where NLP gets its role: a lot of clinically relevant information is only in narrative text and not in coded fields. Family history, clinician assessment and adverse effects, social context and patient preferences are rarely documented. This is vital as personalisation is not just biological markers; functional status and life circumstances, as well as previous treatment tolerance, affect definition of the right treatment for a particular patient. An EHR and NLP powered clinical decision-support system can recommend further testing, alert to treatment risks, identify missed opportunities in care, or help find a match for a patient and a treatment or clinical trial.^[25,26] But, it can be challenging to ensure that these tools are effective without also ensuring that the workflow is effective. In other words, opaque, too frequent or hard-to-act-on alerts, no matter how technically accurate, will be ignored if they are not designed as part of a broader, sociotechnical system, but as a standalone predictive engine.^[8-10]

11. WEARABLES, REMOTE MONITORING, AND DIGITAL PHENOTYPING

Continuous or near-continuous monitoring, whether via wearable sensors, via a smartphone, via a device at home, or via a patient-reported outcome (PRO), has been a major enabler of the standard of personalized medicine in routine practice. These tools give high frequency information on activity, sleep, heart rate, glucose, rhythm disturbances and symptoms and medication adherence.^[27,28] Based on this data, AI can set up a patient-specific baseline and then alert clinicians when it detects that a patient is deviating from the baseline which could be a sign of disease deterioration, toxicity, or loss of disease control.^[5,6,12] What really matters is that personalization does not involve a series of episodic clinic visits, but rather evolves toward something more of a process. While AI-enabled wearables hold promise in chronic illness and other areas, such as monitoring rehabilitation, neurodegenerative disease, diabetes management, and cardiology, there are real issues to be tackled: privacy, who owns the data, quality of the signals and behavioral bias.^[5,6] As with many of the other uses listed above, the potential of a technology is not necessarily a reflection of its value or equity to patients who may not have access to the technology or not use it on a regular basis.^[8,9]

12. ROLE OF GENERATIVE AI

Generative AI is one of the newer trends in personalized medicine that has garnered a great deal of interest. For

instance, in the context of personalized medicine, large language models can help summarize patient information, integrate multiple sources of data, and process large volumes of patient information for healthcare professionals without compromising identifiable patient information.^[7,16,29,30] In some cases, the use of individual planning tools can occur without exposing identifiable patient information, which can further aid in the integration of patient information and improve efficiency within healthcare settings.^[7,16] The risks here are not that small, however. Overconfidence, hidden bias, hallucination, and lack of understanding of the source are all real dangers in a personalized-medicine setting because a slight patient-specific detail could mean a different treatment for a patient.^[7,16,31,32] The control of synthetic data and generative outputs is still an open issue. For now, generative AI is a tool and service that can be very helpful in its ability to preserve sensitive structure from the data it was trained on or to reproduce biases that were built into the training data, but not a decision maker.^[7-9]

13. APPLICATIONS ACROSS CLINICAL SPECIALTIES

The most obvious example of personalized medicine using AI is oncology, where cancer is so variable and is already treated via biomarker-based treatment decisions. AI has been applied in tumor classification, radiogenomics, digital pathology, biomarker discovery, prediction of tumor recurrence and estimation of treatment response, including personalisation of immunotherapy.^[5,13,14,17] Recent studies indicate that multimodal models that integrate genomics, transcriptomics, radiomics, pathomics and clinical information can outperform single-marker models in retrospective settings, while prospective validation remains in its infancy.^[15] In the field of neuroscience, AI is increasingly being utilized for more precise classification of disease and prediction of differential treatment response in disorders with similar clinical presentations, such as in neurology and psychiatry.^[5,6,39] In the field of imaging, AI is being used to interpret CT scans and MRIs.^[44,45] AI's ability to tailor care and adjust doses could also transform diagnosis for rare diseases, as AI can be used to match phenotypic and genotypic patterns amongst widely-dispersed cases that no single clinician would likely encounter enough of to recognise on their own.^[1,5,11,38] Older individuals suffering from multiple chronic conditions are a key frontier of particular importance.^[39,40] Well, you should think about that as you contemplate a review in 2026, because it's not just about being really precise, it's about being really precise in real patients' lives.^[8]

14. ETHICAL, LEGAL, AND SOCIAL CONSIDERATIONS

Ethics and laws are deeply intertwined with personalized medicine using AI, as patient data is used and the decisions made by algorithms are consequential. Improper use of these can not only negatively impact the

patient, but also the families or communities of the patient — so protecting patient privacy, both as part of consent and secondary use, and governing data sharing and re-identification risks, is not a peripheral matter, it is a core requirement for doing this well.^[8-10] Equality of attention must be given to bias and fairness. That would be a real failure of the personalized-medicine promise: to make medical interventions more personalized, less models that would simply exacerbate inequalities rather than reduce them, for those who are already shortchanged.^[8-10] This has shifted the focus of responsible modeling to the middle of the sphere of subgroup validation, fairness auditing and representative data collection. In addition, there is no definitive response regarding interpretability and accountability. In the case of chemotherapy, anti-coagulation or surgery, of course, clinicians will be reluctant to use opaque systems. The issue of responsibility is increasingly salient when systems are used to make recommendations that have adverse impacts, as the systems become more autonomous and more deeply involved in decision making.^[8,10]

15. PRIVACY-PRESERVING AND FEDERATED APPROACHES

Collaboration with other institutions is often necessary for personalized medicine because the data that is needed is broad and diverse; but sharing patient-level data directly increases privacy concerns and legal challenges. This has captured the interest of many researchers interested in privacy-preserving methods for training models across institutions without sharing the raw data, particularly in low-resource settings, underrepresented populations, and/or rare diseases, where the data available at any individual institution is too small to train a robust model. Four themes kept recurring in the 2026 systematic review that looked at the ethics of federated learning in healthcare: algorithmic fairness, privacy preservation, governance, and equitable access to computational resources.^[18] These are directly applicable to personalized medicine; collaboration and privacy protection is only feasible if it is also fair, based on the algorithm, and offering fair benefits to the institutions and patient groups involved. Federated learning is not a technology solution *per se* that answers these questions immediately; it has its own governance and standardization requirements.^[18] However, with the advent of personalized medicine and increasing public awareness of the need to protect data, these techniques will become increasingly important, not less.^[7,10,18] Rather than technical claims made by the tool builders themselves, however, whether they do well will depend on transparency and independent validation.

16. TRANSLATIONAL AND IMPLEMENTATION BARRIERS

Personalized medicine relies on very broad, very diverse data, and often working with other institutions is unavoidable; but sharing patient-level data directly creates privacy risk and legal hurdles¹⁸. Despite the

number of publications on federated learning and related privacy-preserving methods, there are still numerous AI systems in personalized medicine that are not yet in common clinical use. This is often a problem, in that models trained at a single institution, or even on highly curated datasets, frequently drop in accuracy once they encounter new populations, devices, workflows or laboratory conditions, which is particularly true in personalized medicine, where the objective is not to achieve average accuracy across a population, but rather to obtain reliable performance in clinically meaningful subgroups.^[8,10] Fragmentation of data is another challenge.^[10] The challenges here are an organizational rather than technical one: Omics data, imaging, pathology and EHR records are usually stored in distinct systems, with different standards.^[5,8,12] To convert them into a usable clinical pipeline, a significant investment in interoperability, annotation, governance and informatics infrastructure is required. While some models perform well during retrospective evaluation, those models may end up performing poorly in real life if they don't align with how care is actually provided.^[8-10] Improvements in this area not only rely on improving algorithms, but on implementation science, user-centered design and institutions willing to embrace the change.

17. FUTURE DIRECTIONS

There are a couple of trends that appear set to define the future of this field. Such systems are able to learn from a combination of genomics, imaging, pathology, laboratory data, text and longitudinal monitoring data at once, as opposed to any individual approach which is more limited and potentially less clinically representative of the patient.^[5,6,12] The second is growing use of generative AI and foundation models for data synthesis, data communication and cross-modal reasoning, which can alleviate data scarcity and workflow burden but their clinical impact will rely on the strict bench marking, careful tracking of provenance, and robust safeguards against potential risks. The third is ongoing growth of privacy-preserving collaboration via federated learning and other techniques, which may enable larger groups to contribute to model development, without the need for complete centralization of data.^[10,18] But perhaps most important is augmentation of the human. In this scenario, the most believable application of AI for personalized medicine is not replacing the clinician, but managing complexity, measuring uncertainty and working together to make better decisions.^[5,6,8] In this way, the success of personalized medicine will be as much about the trust, communication, and governance as it will be about any technical feat.

18. CONCLUSION

One way that AI has seeped into personalized medicine is by making it possible to integrate molecular, phenotypic, clinical and behavioral information into insights specific to one patient. These advances are seen in oncology, cardiovascular medicine, neurology, chronic disease management, rare disease and the

emerging field of multimorbidity management. Meanwhile, there are persisting true methodological and ethical restrictions in the field. Overall, AI is transforming personalized medicine, but its impact and usefulness will hinge on its ability to be a safe, fair, and clinically practical addition to care, not just a pretty, but impractical tool.

ACKNOWLEDGEMENTS

The authors extend their gratitude to The Erode College of Pharmacy & Research Institute, Tamil Nadu, India for providing necessary facilities and support for this review work.

Author contribution

Study Conception and Design Data Collection Chittesh, Thibiraj: Main Manuscript prepared by Chittesh, Thibiraj, Jeyaprabha*: Draft manuscript review by Dr.sambath kumar. All authors reviewed the results and approved the final version of the manuscript.

Funding

“none to declare.”

Conflict of interest

“none to declare.”

Ethics approval

“none to declare.”

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author (s) used Quillbot to improve the language, grammar and readability of the manuscript. The author(s) reviewed and edited the output as necessary and accept full responsibility for the content of the final manuscript.

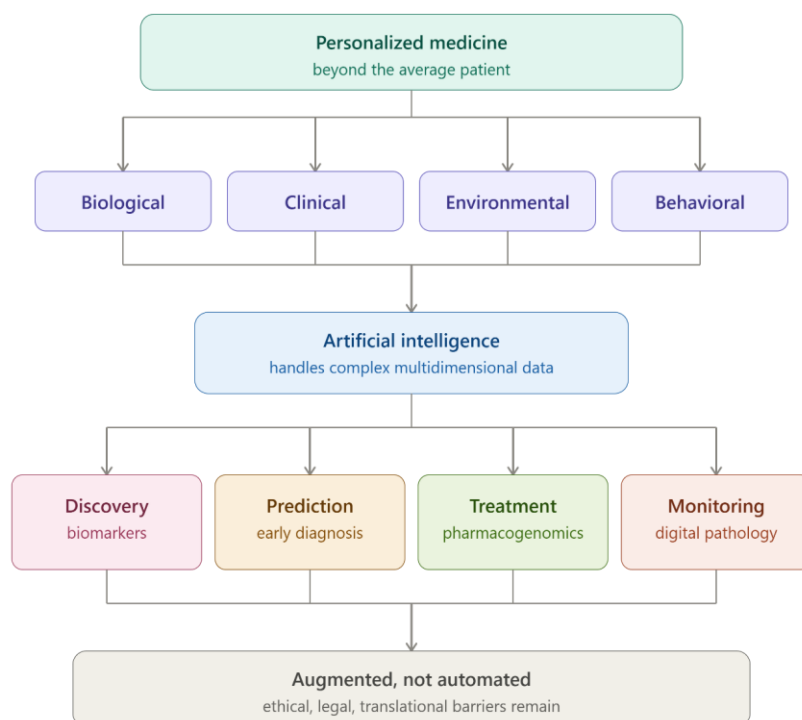


Figure 1: Conceptual overview of how patient data domains and artificial intelligence converge to support personalized medicine.

REFERENCES

1. Stafie CS, Sufaru IG, Ghiciuc CM, Stafie II, Sufaru EC, Solomon SM, et al. Exploring the intersection of artificial intelligence and clinical healthcare: a multidisciplinary review. *Diagnostics*, 2023; 13: 1995. doi:10.3390/diagnostics13121995
2. Garcia-Agundez A, Garcia-Martin E, Eickhoff C. Editorial: the potential of machine-learning in pharmacogenetics, pharmacogenomics and pharmacoepidemiology: volume II. *Front Pharmacol*, 2023; 14: 1277561. doi:10.3389/fphar.2023.1277561
3. Krittanawong C, Johnson KW, Tang WW. How artificial intelligence could redefine clinical trials in cardiovascular medicine: lessons learned from oncology. *Per Med*, 2019; 16: 83-88. doi:10.2217/pme-2018-0130

4. Roosan MR, Mettu R. Editorial: machine learning advancements in pharmacology: transforming drug discovery and healthcare. *Front Pharmacol*, 2025; 16: 1583486. doi:10.3389/fphar.2025.1583486
5. He X, Liu X, Zuo F, Shi H, Jing J. Artificial intelligence-based multi-omics analysis fuels cancer precision medicine. *Semin Cancer Biol*, 2023; 88: 187-200. doi:10.1016/j.semcancer.2022.12.009
6. Rezayi S, Niakan Kalhori S, Saeedi S. Effectiveness of artificial intelligence for personalized medicine in neoplasms: a systematic review. *Biomed Res Int*, 2022; 2022: 7842566. doi:10.1155/2022/7842566
7. Thirunavukarasu AJ, Ting DSJ, Elangovan K, Gutierrez L, Tan TF, Ting DSW. Large language models in medicine. *Nat Med*, 2023; 29(8): 1930-1940. doi:10.1038/s41591-023-02448-8
8. Haider SA, Bornha S, Gomez-Cabello CA, Pressman SM, Haider CR, Forte AJ. The algorithmic divide: a systematic review on AI-driven racial disparities in healthcare. *J Racial Ethn Health Disparities*, 2026; 13(1): 188-217. doi:10.1007/s40615-024-02237-0
9. van de Sande D, van Bommel J, Fung Fen Chung E, Gommers D, van Genderen ME. Algorithmic fairness audits in intensive care medicine: artificial intelligence for all? *Crit Care*, 2022; 26: 322. doi:10.1186/s13054-022-04197-5
10. Williams DKA Jr, Graifman G, Hussain N, Amiel M, Tran P, Reddy A, et al. Digital pathology, deep learning, and cancer: a narrative review. *Transl Cancer Res*, 2024; 13(5): 2544-2560. doi:10.21037/tcr-23-964
11. De La Vega FM, Chowdhury S, Moore B, Frise E, McCarthy J, Hernandez EJ, et al. Artificial intelligence enables comprehensive genome interpretation and nomination of candidate diagnoses for rare genetic diseases. *Genome Med*, 2021; 13: 153. doi:10.1186/s13073-021-00965-0
12. Wei L, Niraula D, Gates EDH, Fu J, Luo Y, Nyflot MJ, et al. Artificial intelligence (AI) and machine learning (ML) in precision oncology: a review on enhancing discoverability through multiomics integration. *Br J Radiol*, 2023; 96(1150): 20230211. doi:10.1259/bjr.20230211
13. Rabilloud N, Allaume P, Acosta O, De Crevoisier R, Bourgade R, Loussouarn D, et al. Deep learning methodologies applied to digital pathology in prostate cancer: a systematic review. *Diagnostics*, 2023; 13: 2676. doi:10.3390/diagnostics13162676
14. He Y, Zhao H, Wong STC. Deep learning powers cancer diagnosis in digital pathology. *Comput Med Imaging Graph*, 2021; 88: 101820. doi:10.1016/j.compmedimag.2020.101820
15. Vanguri RS, Luo J, Aukerman AT, Egger JV, Fong CJ, Horvat N, et al. Multimodal integration of radiology, pathology and genomics for prediction of response to PD-(L)1 blockade in patients with non-small cell lung cancer. *Nat Cancer*, 2022; 3: 1151-1164. doi:10.1038/s43018-022-00416-8
16. Omar M, Sorin V, Collins JD, et al. Multi-model assurance analysis showing large language models are highly vulnerable to adversarial hallucination attacks during clinical decision support. *Commun Med (Lond)*, 2025; 5: 330. doi:10.1038/s43856-025-01021-3
17. Liu H, Bai Y, Wang Z, Yin S, Gong C, Wang B. Multimodal deep learning for predicting PD-L1 biomarker and clinical immunotherapy outcomes of esophageal cancer. *Front Immunol*, 2025; 16: 1540013. doi:10.3389/fimmu.2025.1540013
18. Mir BA, Abbas SR, Lee SW. Federated learning in healthcare ethics: a systematic review of privacy-preserving and equitable medical AI. *Healthcare (Basel)*, 2026; 14(3): 306. doi:10.3390/healthcare14030306
19. Annunziata S, Treglia G. Editorial: radiomics and artificial intelligence in radiology and nuclear medicine. *Front Med (Lausanne)*, 2023; 10: 1216434. doi:10.3389/fmed.2023.1216434
20. Huang H. Editorial: the application of radiomics and artificial intelligence in cancer imaging. *Front Oncol*, 2022; 12: 864940. doi:10.3389/fonc.2022.864940
21. Chen Z, Zhang H, Zhang PJZ, Bai HX, Li X. Editorial: advances of radiomics and artificial intelligence in the management of patients with central nervous system tumors. *Front Oncol*, 2023; 13: 1081301. doi:10.3389/fonc.2023.1081301
22. Stefano A, Bertelli E, Comelli A, Gatti M, Stanzione A. Editorial: radiomics and radiogenomics in genitourinary oncology: artificial intelligence and deep learning applications. *Front Radiol*, 2023; 3: 1325594. doi:10.3389/fradi.2023.1325594
23. Guo Y, et al. From images to genes: radiogenomics based on artificial intelligence to achieve non-invasive precision medicine in cancer patients. *Adv Sci (Weinh)*, 2025; 12. doi:10.1002/advs.202408069
24. Roshkovan L, Kontos D. State of the art: radiomics and radiomics-related artificial intelligence on the road to clinical translation. *BJR Open*, 2023; 6(1): tzad004. doi:10.1093/bjro/tzad004
25. Eguia H, Sánchez-Bocanegra CL, Vinciarelli F, Alvarez-Lopez F, Saigí-Rubió F. Clinical decision support and natural language processing in medicine: systematic literature review. *J Med Internet Res*, 2024; 26: e55315. doi:10.2196/55315
26. Hossain E, Rana R, Higgins N, Soar J, Barua PD, Pisani AR, et al. Natural language processing in electronic health records in relation to healthcare decision-making: a systematic review. *Comput Biol Med*, 2023; 155: 106649. doi:10.1016/j.compbiomed.2023.106649
27. Emish M, Young SD. Remote wearable neuroimaging devices for health monitoring and neurophenotyping: a scoping review. *Biomimetics (Basel)*, 2024; 9: 237. doi:10.3390/biomimetics9040237
28. Dlima SD, Shevade S, Menezes SR, Ganju A. Digital phenotyping in health using machine learning approaches: scoping review. *JMIR Biomed Eng*, 2022; 3(1): e39618. doi:10.2196/39618

29. Lee P, Bubeck S, Petro J. Benefits, limits, and risks of GPT-4 as an AI chatbot for medicine. *N Engl J Med*, 2023; 388(13): 1233-1239. doi:10.1056/NEJMSr2214184
30. Singhal K, Azizi S, Tu T, Mahdavi SS, Wei J, Chung HW, et al. Large language models encode clinical knowledge. *Nature*, 2023; 620(7972): 172-180. doi:10.1038/s41586-023-06291-2
31. Chang CT, Srivathsa N, Bou-Khalil C, Swaminathan A, Lunn MR, Mishra K, et al. Evaluating anti-LGBTQIA+ medical bias in large language models. *PLOS Digit Health*, 2025. doi:10.1371/journal.pdig.0001001
32. Ji Z, Lee N, Frieske R, Yu T, Su D, Xu Y, et al. Survey of hallucination in natural language generation. *ACM Comput Surv*, 2023; 55(12): 1-38. doi:10.1145/3571730
33. Li QY, Tang BH, Wu YE, Yao BF, Zhang W, Zheng Y, et al. Machine learning: a new approach for dose individualization. *Clin Pharmacol Ther*, 2024; 115: 727-744. doi:10.1002/cpt.3049
34. Zhang S, Jiang J, Luo Y, Liu G, Hu S, Wan S, et al. Artificial intelligence in electrocardiogram-based prediction of heart failure: a systematic review and meta-analysis. *Front Cardiovasc Med*, 2026; 13: 1659298. doi:10.3389/fcvm.2025.1659298
35. Dhingra LS, Aminorroaya A, Pedroso AF, Khunte A, Sangha V, McIntyre D, et al. Artificial intelligence-enabled prediction of heart failure risk from single-lead electrocardiograms. *JAMA Cardiol*, 2025; 10(6): 574-584. doi:10.1001/jamacardio.2025.0492
36. Desai AS, Pandey A, Suratekar R, Ahmad FS, Alger HM, Anto AG, et al. Predicting heart failure from 12-lead ECGs using AI: a HeartShare/AMP-HF pooled cohort analysis. *J Am Coll Cardiol*, 2025. doi:10.1016/j.jacc.2025.10.065
37. Shen W, Moon I, Nguyen TH, Li MM, Huang Y, Nair N, et al. Generalizable AI predicts immunotherapy outcomes across cancers and treatments. *Nat Med*, 2026. doi:10.1038/s41591-026-04502-7
38. Qin B, Quan Q, Wu J, Liang L, Li D. Diagnostic performance of artificial intelligence to detect genetic diseases with facial phenotypes: a protocol for systematic review and meta-analysis. *Medicine (Baltimore)*, 2020; 99(27): e20989. doi:10.1097/MD.00000000000020989
39. Zhao Z, Chuah JH, Lai KW, Chow CO, Gochoo M, Dhanalakshmi S, et al. Conventional machine learning and deep learning in Alzheimer's disease diagnosis using neuroimaging: a review. *Front Comput Neurosci*, 2023; 17: 1038636. doi:10.3389/fncom.2023.1038636
40. Liu Xz, Duan M, Huang Hd, Zhang Y, Xiang Ty, Niu Wc, et al. Predicting diabetic kidney disease for type 2 diabetes mellitus by machine learning in the real world: a multicenter retrospective study. *Front Endocrinol (Lausanne)*, 2023; 14: 1184190. doi:10.3389/fendo.2023.1184190
41. Taliaz D, Spinrad A, Barzilay R, et al. Optimizing prediction of response to antidepressant medications using machine learning and integrated genetic, clinical, and demographic data. *Transl Psychiatry*, 2021; 11: 381. doi:10.1038/s41398-021-01488-3
42. Chen B, Jiao Z, Shen T, et al. Early antidepressant treatment response prediction in major depression using clinical and TPH2 DNA methylation features based on machine learning approaches. *BMC Psychiatry*, 2023; 23: 299. doi:10.1186/s12888-023-04791-z
43. Jaworska N, De La Salle S, Ibrahim MH, Blier P, Knott V. Leveraging machine learning approaches for predicting antidepressant treatment response using electroencephalography (EEG) and clinical data. *Front Psychiatry*, 2019; 9: 768. doi:10.3389/fpsy.2018.00768
44. Shui L, Ren H, Yang X, Li J, Chen Z, Yi C, et al. The era of radiogenomics in precision medicine: an emerging approach to support diagnosis, treatment decisions, and prognostication in oncology. *Front Oncol*, 2020; 10: 570465. doi:10.3389/fonc.2020.570465
45. Cuocolo R, Comelli A, Stefano A, Benfante V, Dahiya N, Stanzione A, et al. Deep learning whole-gland and zonal prostate segmentation on a public MRI dataset. *J Magn Reson Imaging*, 2021; 54: 452-459. doi:10.1002/jmri.27585
46. Bertelli E, Mercatelli L, Marzi C, Pachetti E, Baccini M, Barucci A, et al. Machine and deep learning prediction of prostate cancer aggressiveness using multiparametric MRI. *Front Oncol*, 2022; 11: 802964. doi:10.3389/fonc.2021.802964
47. Cuocolo R, Verde F, Ponsiglione A, Romeo V, Petretta M, Imbriaco M, et al. Clinically significant prostate cancer detection with biparametric MRI: a systematic review and meta-analysis. *AJR Am J Roentgenol*, 2021; 216: 608-621. doi:10.2214/AJR.20.23219
48. Woodard GA, Ray KM, Joe BN, Price ER. Qualitative radiogenomics: association between Oncotype DX test recurrence score and BI-RADS mammographic and breast MR imaging features. *Radiology*, 2018; 286: 60-70. doi:10.1148/radiol.2017162333
49. Gevaert O, Echegaray S, Khuong A, Hoang CD, Shrager JB, Jensen KC, et al. Predictive radiogenomics modeling of EGFR mutation status in lung cancer. *Sci Rep*, 2017; 7: 41674. doi:10.1038/srep41674
50. Zhou M, Leung A, Echegaray S, Gentles A, Shrager JB, Jensen KC, et al. Non-small cell lung cancer radiogenomics map identifies relationships between molecular and imaging phenotypes with prognostic implications. *Radiology*, 2018; 286: 307-315. doi:10.1148/radiol.2017161845