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Review Article

AI in Personalized Medicines: Opportunities and Challenges

Ayushi Gupta, Anurag Sharma*, Neelkanth M. Pujari, Akash Ved

Faculty Of Pharmacy, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh - 226031, India.

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ABSTRACT

The integration of Artificial Intelligence (AI) in personalized medicine has revolutionized healthcare by enabling precise, data-driven, and patient-specific treatment strategies. Artificial intelligence (AI) has the potential to revolutionize healthcare by enabling personalized medicine and improving disease diagnosis. AI-powered algorithms, particularly those leveraging machine learning (ML) and deep learning (DL), have enhanced the ability to analyse vast datasets, uncover hidden patterns, and generate predictive models that facilitate early disease detection, drug discovery, and customized treatment regimens. Emerging technologies such as explainable AI (XAI) aim to enhance transparency in decision-making, allowing physicians and patients to better understand AI-generated recommendations. The convergence of AI with other innovations, such as blockchain for secure data management and the Internet of Medical Things (IoMT) for real-time patient monitoring, further strengthens its role in personalized medicine. In 2019, the International Consortium for Personalised Medicine (ICPerMed) developed a vision on how the use of personalized medicine (PM) approaches will promote "next-generation" medicine in 2030 more firmly centred on the individual's personal characteristics, leading to improved health outcomes within sustainable healthcare systems through research, development, innovation, and implementation for the benefit of patients, citizens, and society. This includes engagement strategies, collaboration frameworks, infrastructure development, education and training programs, ethical considerations, resource allocation guidelines, regulatory compliance, and data management and privacy. This paper explores the transformative potential of AI in personalized medicine, analysing its key applications, limitations, and future prospects. A thorough examination of current AI-driven methodologies, case studies, and policy considerations will provide a holistic understanding of the evolving landscape.

INTRODUCTION

Personalized medicine, also known as precision medicine, is a rapidly evolving medical approach that seeks to personalize healthcare by taking into account a patient's unique characteristics at molecular, physiological, ecological, and behavioural levels. PM medicine is defined as the movement involving what the National Research Council initially called the development of "a New Taxonomy of human disease based on molecular biology," or a revolution in health care triggered by knowledge gained from sequencing the human genome (*G. S. Ginsburg and J. J. McCarthy,2001)*. Personalized medicine promises to revolutionize the patient treatment by offering tailored medical services to the individual characteristics of each patient. AI focuses on prevention rather then reaction by decreasing adverse drug reaction and patient outcome by reducing prescription errors (Figure 1). The new era of efficiency and cost-effectiveness in creating tailored marketing materials by the advent of Generative Artificial

***Corresponding Author:** Anurag Sharma

Address: Faculty Of Pharmacy, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh - 226031, India.

Email ✉: sharmaanurag6387@gmail.com

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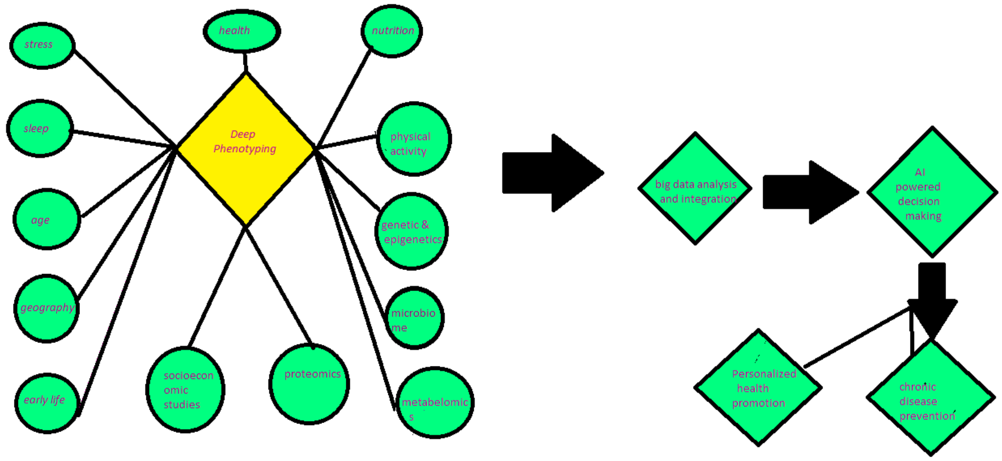

Figure 1: PM in the era of AI

Intelligence (GenAI) technologies, particularly Large Language Models (LLMs). An emerging field in computer science called artificial intelligence (AI) is being used more and more to carry out tasks that require human-like intelligence, including the ability to reason logically, solve complicated issues, and do learning analysis using large amounts of data. It is impossible to overestimate the importance of AI in the healthcare industry, especially in fields like telemedicine and patient monitoring where it is causing revolutionary breakthroughs. The rapid development of Natural Language Processing (NLP) algorithms is one of the most exciting areas of AI in healthcare. The use of computer vision algorithms to analyze medical imaging, including MRIs and CT scans, is another noteworthy achievement. Healthcare professionals may diagnose patients more quickly and accurately by using AI to classify and identify illnesses (*Gulshan, V.et al., 2016)*. The following are the PM goals as they relate to public health:

- To group populations in order to determine which ones gain the most from a particular treatment;
- To reduce the quantity of patients who receive needless treatment.

Data and security, analytics and insights, and shared expertise are the three key tenets for the effective implementation of artificial intelligence in healthcare.

Methodology for Developing PM Using AI

The methodology for developing a framework for using AI in personalized medicine (PM) to optimize treatment plans follows a systematic approach based on the PRISMA method. The objective is to leverage AI's capabilities in data analysis and pattern recognition to tailor treatment plans to individual patients, ensuring more effective and efficient outcomes. The results of the AI integration are evaluated. This involves testing the framework in real-world clinical settings, measuring its effectiveness in optimizing treatment plans, and assessing its impact on patient outcomes. The evaluation process includes performance metrics such as accuracy, patient satisfaction, and cost-effectiveness. Feedback is collected from healthcare providers and patients to continuously refine the AI-based framework.

Steps Includes:-

- Identifying the main Statement Problem,
- Then, literature Review is made through,
- AI Integration Strategy is defined,
- Basic Framework is developed for PM,
- Then finally, Evaluation of results is made.

Through these steps (Figure 2), the methodology seeks to establish a robust and scalable AI-driven framework for personalized medicine, optimizing treatment plans for better healthcare outcomes.

Conceptual Framework Design

The conceptual framework for developing an AI-based system to optimize treatment plans in personalized medicine is anchored in a comprehensive, patient-centered approach that aligns technological innovation with individualized healthcare delivery. The proposed framework envisions a dynamic ecosystem where artificial intelligence (AI) serves as the analytical engine that transforms diverse and complex health data into actionable insights, enabling clinicians to make well-informed, tailored treatment decisions for each patient *(Adewale, et al., 2022, Uwaifo, 2020).* It is designed to facilitate the full integration of AI with the principles of personalized medicine—namely, the use of biological, genetic, lifestyle, and environmental data to inform medical care and predict outcomes with high precision (Figure 3).

Applications of AI in Personalized Medicine

AI has been applied in various aspects of personalized medicine, including diagnosis, prognosis, treatment optimization, and patient monitoring. Below, we discuss some of the key applications:

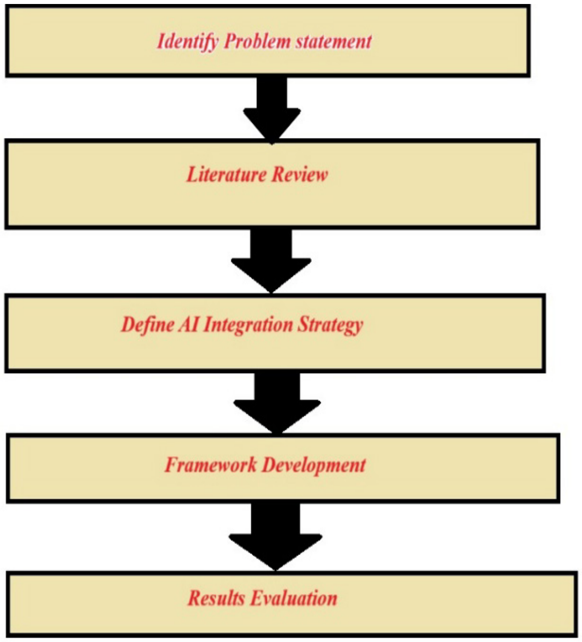

Figure 2: PRISMA Flow Chart of the Study Methodology

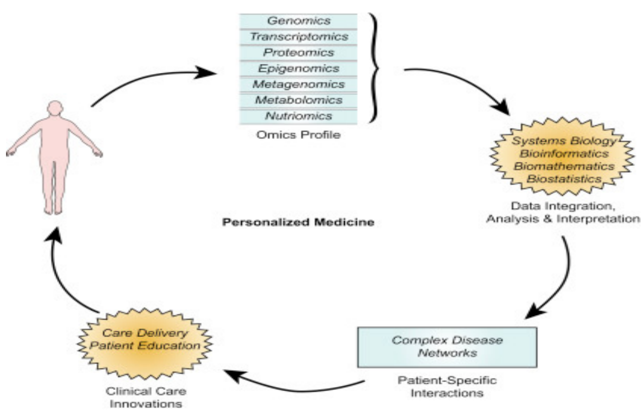

Figure 3: Basic Framework of PM

Diagnosis and Prognosis

The accuracy and speed of medical diagnosis have been demonstrated to be greatly enhanced by AI algorithms, especially those based on machine learning and deep learning. AI-powered imaging technologies, for instance, can accurately identify abnormalities in medical pictures, including MRIs, CT scans, and X-rays. These resources can help radiologists spot early indicators of illnesses like cancer, heart disease, and neurological issues.

Treatment Optimization

AI has the potential to optimize treatment strategies by predicting how individual patients will respond to specific therapies. For example, ML algorithms can analyze clinical and genomic data to identify the most effective treatment options for cancer patients. This approach, known as precision oncology, aims to match patients with targeted therapies based on the molecular profile of their tumors.

Patient Monitoring and Management

Continuous patient health status monitoring is made possible by wearable technology and mobile health apps driven by AI. Vital signs, physical activity, and other health metrics can be recorded in real time by these devices. Which can be analyzed using AI algorithms to detect early signs of deterioration or complications.

Virtual Assistant Chatbots for Patient Support and Education

Virtual assistant chatbots can provide personalized medical support and education to patients based on their individual needs and preferences. Chatbots can learn from patient interactions and modify their responses to fit the patient's language and style by using machine learning algorithms and Natural Language Processing (NLP), which makes the user seem more engaging and natural. Chatbots are available around-the-clock and can assist patients in getting the support and information they require at the appropriate time (*Aggarwal, A. et al., 2023, Kurniawan, M. H. et al.)* Chatbots can assist patients in getting the support and information they require at the right time because they are available around-the-clock. Artificial intelligence and machine learning are already being used by a number of online chatbots, including Individualized health information and support are available for minor illnesses, long-term conditions, and mental health issues from Symptoms, Babylon Health, AI Health, Iodine, Molly, and others (*Abd Rahman, R. et al., 2020)*

Interoperability of data is a significant problem. It can be challenging to share and integrate data when patient medical records are kept in disparate electronic health record (EHR) systems that lack common standards and protocols (*Bertagnolli, M. M. et al.,2020).*

Data standardization protocols like HL7 FHIR and health information exchanges (HIEs) are constantly developing to solve this issue. The second issue is data standardization. Data integration becomes more difficult when different healthcare organizations and EHR systems use different data formats and coding schemes. Promoting uniform data standards and coding schemes throughout the sector is necessary to get past these challenges (*Kiourtis, A., et al., 2020).*

Wearable Technology and Sensors for Telepatient and Real-time Patient Monitoring

Medical practitioners may now continuously monitor vital signs and other biometric data thanks to wearable technology and sensors, which makes remote patient care and real-time patient monitoring possible *(He, T. & Lee, C.,2021).*Take smartwatches, for example. Another small and lightweight option are wearable sensors, which can be used to monitor vital signs and health metrics such as body temperature, heart rate, blood pressure, respiration rate, blood oxygen saturation, and physical activity. They can also be worn on the body or integrated into jewelry, clothes, or other items. For in-depth examination, the sensors wirelessly transmit the data to a central monitoring station. Additionally, wearable technology and integrated sensors can be used by smartphone apps. Real-time patient health status monitoring is also possible with smart home appliances like thermostats and smart speakers. There are numerous potential advantages for both patients and healthcare professionals when wearable technology and sensors are used for real-time patient monitoring *(Nguyen, T. N. et al., 2023)*. Patients may feel more confident and at ease knowing that their health is being monitored and that any changes in their condition can be quickly noticed. Specifically, when monitoring blood pressure, wrist-worn devices may be impacted by user movement and wrist position, which could result in false readings. On the other hand, upper-arm cuffs are typically thought to be more accurate for taking blood pressure. Additionally, to better protect patient privacy and data security, technologies for anonymization and encryption are being deployed.

Predictive Models for Disease Progression and Patient Risk Stratification

Predictive models for disease progression and patient risk stratification utilize machine learning algorithms to analyze patients' medical history, genetic information, and information to forecast their chance of contracting specific illnesses or the course of pre-existing conditions. Additionally, these models can identify patients who are at risk of contracting specific diseases, allowing medical professionals to lower risk by putting preventative measures in place (*Cai, Y. et al., 2024).* Additionally, they are employed to predict how patients' existing illnesses may develop, enabling medical professionals to modify treatment regimens as necessary. In order to help physicians better comprehend the course of Alzheimer's disease and modify treatment regimens appropriately, models for forecasting the course of diseases and identifying patient risk.

By using patient data including blood pressure, cholesterol, and genetic information, cardiovascular disease risk prediction models can estimate the likelihood of heart disease, helping physicians identify high-risk patients and implement early intervention strategies (*D'Agostino, R. B.,et al., 2024).*It is equally important to make sure that the application of these models adheres to the highest ethical standards, is safeguarded by informed patient consent, and is backed by stringent oversight and regulatory frameworks meant to stop any possible abuse against particular patient populations *(Zheng, Y. et al., 2022)*.

A crucial area of healthcare is the recommendation of customized treatments based on patient data and patient risk stratification factors (Figure 4) are essential tools that enable healthcare professionals to proactively identify patients at high risk of particular diseases and carry out

Figure 4: Factors For Patient's Risk Stratification Engine

preventive interventions *(Yarborough, B. J. H. et al., 2022)*. Ensuring that the use of these models complies with the highest ethical standards, is protected by informed patient consent, and is supported by strict oversight and regulatory frameworks intended to prevent any potential misuse or discriminatory practices against specific patient populations is equally expedient *(Obermeyer, Z. & Emanuel, 2016).*

Personalized Treatment Recommendations based on Patient Data

Given their potential to enhance patient outcomes and lower medical expenses, personalized treatment recommendations based on patient data represent a highly significant area of healthcare *(Liu, Z. et al., 2004)*

Gene expression profiles, single-nucleotide polymorphisms (SNPs), and whole-genome sequencing are examples of genomic data that offer vital insights into the molecular causes of diseases and how each patient reacts to treatment.

Through the integration of information on gene mutations, copy number variations, and epigenetic modifications, these models are able to pinpoint particular biomarkers that are associated with the effectiveness of treatment.

The patient's chances of a successful outcome can then be increased by using this information to suggest the best course of treatment *(Cuocolo, R. et al., 2020).*

Pharmacogenomics is a quickly developing field that examines how genetic variations impact drug efficacy and possible side effects, integrating genetic information to optimize drug therapy (*Ryan, D. K. et al., 2024)*.

Additionally, pharmacogenomic data can help identify patients who might experience adverse drug reactions, allowing for preventive measures or alternative treatment strategies (Table 1).

Healthcare professionals can improve clinical outcomes and patient care by integrating pharmacogenomic data into individualized treatment plans *(Varnai, R. et al, 2019)*.

Automatic Reminders and Scheduling of Appointments

The healthcare industry can benefit greatly from automated appointment scheduling and reminders, which can increase patient compliance and reduce provider workload (*Werner, K. et al., 2023)*.

Based on prior appointment schedules and patient history, these platforms employ artificial intelligence to evaluate patient data and suggest the best times for appointments *(Kalinin AA et al., 2018).*

This sophisticated analysis lowers the possibility of missed appointments or the need for rescheduling, improving results and boosting system efficiency. Artificial intelligence (AI) can, for instance, spot trends in patient behavior and appointment history that conventional scheduling systems might miss, improving scheduling to better suit patient demands and provider availability.

PatientPop, Zocdoc, and Vyasa are examples of real-world platforms that use AI to improve automated appointment scheduling and reminders. These platforms use artificial intelligence to analyze patient data and recommend the most appropriate appointment times based on patient history and previous appointment schedules.

The Transformative Impact of AI on Healthcare

Numerous facets of healthcare are being transformed by artificial intelligence (AI), with current research and development concentrating on a few crucial areas. Deep learning models are now being utilized in medical imaging and diagnosis to help identify and diagnose illnesses in pictures from CT, MRI, and X-ray tests. AI systems, for instance, are used to quickly and accurately detect early indicators of neurological problems, cardiovascular ailments, and cancer. AI supports the analysis of lifestyle, demographic, and genetic data in personalized medicine to offer tailored therapy suggestions. This method is especially helpful in cancer since AI can forecast how a patient will react to various chemotherapy medications, resulting in more customized and efficient treatment regimens.

Challenges in the Implementation of AI in Personalized Medicine

Data privacy and security

Data breaches, in which hackers or other malevolent actors obtain patient data (such as insurance information or medical records) without authorization, are one of the many data security risks that could seriously harm healthcare providers' finances and reputations. Patient data may be exposed to misuse or illegal access if it is not adequately encrypted, either in transit or at rest.

Algorithmic bias

The quality of the data that AI systems are trained on determines how well they perform. Disparities in healthcare outcomes could occur from biased algorithms that use unrepresentative or biased training data. An AI system may not function well for patients from different demographic groups, for instance, if it was trained primarily on data from that group. Healthcare

Table 1: Impact of Pharmacogenomics

Therapy	*Test and its description*	*Clinical Guidance*	*Reference*
Breast Cancer	BRCA1: deleterious BRCA1 or BRCA2 mutants have a high risk of breast and ovarian cancer	Surveillance and chemoprention therapy	Redekop and Mladsi (2013)
Breast Cancer	HER2 : tumors with HER2:overexpression	Recommended use of Tratuzumab	Redekop and Mladsi (2013)
Epilepsy	HLA-B*1502 HLA-B*1502-positive patients show skin reaction on t/t with carbamazepine	Choose other alternative drug ,carbamazepine use may be dangerous	Redekop and Mladsi (2013)
Artial Fibrilation	CYP2C9, VKORC1:Warfarin therapy dose dependent on CYP2C9 and VKORC1 genotypes	Dose of Warfarin	Redekop and Mladsi (2013)
Hepatitis C	HCV RNA: level of viral RNA measured after t/t with interferon alpha and ribavirin	Required duration of t/t	Redekop and Mladsi (2013)
Antiplatelet Medications	CYP2C19: Clopidogel {prodrug} require metabolIc activation by CYP2C19	Alternative drug used for patient with decreased CYP2C19	Mousa et al. (2012)
Immunosuppresive Therapy	Thiopurine methyltransferase(TPMT): Azathioprine{prodrug} convert to mercaptopurine undergo methylation to inactive metabolites by TPMT	Patient have higher risk for toxicity with azathioprine having decresed level of TPMT	Relling et al.(2011)
Kidney Transplants and invasive fungal infections	CYP2C19: Voriconazole metabolism through CYP2C19	Alternative agent used in case of CYP2C19 rapid or poor metabolizer	Guinea et al.(2016)

practitioners need to be aware of potential sources of bias in the data they gather and the algorithms they utilize in order to address concerns about bias and discrimination in AI algorithms. This could entail examining any potential biases in the data, training algorithms on a variety of datasets, and putting policies in place to keep an eye out for and deal with any biases or discrimination that might exist in the algorithms.

Validation and regulatory oversight

For AI algorithms to be safe and effective, validation is essential. This may result in the use of AI tools that have not undergone sufficient testing, which could endanger patients. The Medicines and Healthcare Products Regulatory Agency (MHRA), which is in charge of regulating medical devices in the UK, has its own regulations and approval processes, therefore the regulatory frameworks and approval processes for medical devices may vary *(Lievevrouw, E., Marelli, L. & Van Hoyweghen, 2022).* By publishing recommendations like "Software as a Medical Device (SaMD): Key Definitions" and "SaMD: Clinical Evaluation," groups like the International Medical Device Regulators Forum (IMDRF) have contributed to worldwide harmonization efforts in addition to regulatory authorities. These initiatives help create a consistent framework for the development, evaluation, and regulation of AI-based medical devices globally.

Ethical considerations

The use of AI in healthcare raises several ethical questions, including issues related to patient consent, transparency, and accountability. For example, who is responsible if an AI algorithm makes an incorrect diagnosis or recommends an inappropriate treatment? How can patients be assured that their data is being used ethically and responsibly?

Future Directions

With the increasing demands of the world in the personalized medicines, generative AI has played a great role in revolutionizing it (Figure 5) and has great future directions as follows:-

Multi-Omics Data Integration

The integration of multi-omics data, including genomics, proteomics, and metabolomics, can provide a more comprehensive understanding of disease mechanisms and treatment responses.

Explainable AI Development

Explainable AI (XAI) refers to AI systems that can provide clear and interpretable explanations for their decisions.

Collaboration between Stakeholders

The successful implementation of AI in personalized medicine requires collaboration between various stakeholders, including healthcare providers, researchers, technology companies, and regulatory agencies. This collaboration will be essential for developing standardized protocols, ensuring data privacy, and addressing ethical concerns.

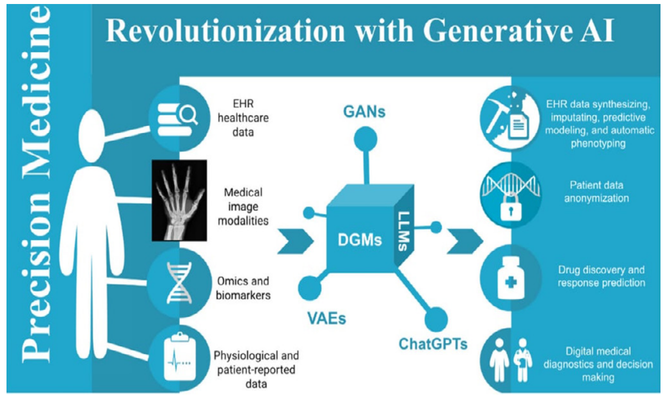

Figure 5: Revolution with Generative AI in PM

CONCLUSION

With the potential to significantly improve patient care and maximize therapeutic results, the introduction of artificial intelligence into the healthcare industry heralds a revolutionary age. However, the ethical, legal, and sociological implications of integrating AI into clinical practice must be carefully considered. Strict policymaking is essential to utilizing AI technologies in a way that promotes accountability and transparency while, most importantly, giving patients' data security and privacy a priority. As this review discusses, the use of personalized medicine significantly depends on AI algorithms. Nonetheless, it is still in its infancy and has several obstacles to overcome, some of which were specifically related to artificial intelligence and covered in this research. However, the algorithms covered in this paper do not address other issues that are crucial to the successful application of customized medicine, such as government laws and the costs of research and implementation. Personalized medicine does, however, present certain difficulties. For example, it has the potential to transform the medical field and practice to the point where some futurists believe that computers and algorithms may eventually replace the majority of the work that doctors currently perform. Last but not least, a successful tailored medicine implementation will enhance the medical field and save countless lives. Only through meticulous governance can we ensure that the benefits of artificial intelligence in healthcare are realized without compromising the trust and well-being of those who seek our care.

Conflict of Interests

None.

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