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AI for Precision Medicine: Integrating Machine Learning in Healthcare

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Abstract

The development of artificial intelligence (AI) and machine learning (ML) has become a new disruptive technology in precision medicine, which allows the provision of tailored treatment plans with the help of sophisticated data analytics, multimodal assimilation, and predictive modelling. It is an empirical review of the recent literature on AI and ML in the context of precision medicine, specifically how they can be used to combine patient genomics, lifestyle data, and clinical records to provide personalised care delivery. The review covers the new advances in genomics, clinical diagnostics, biomarker discovery, personalised therapeutics, and answers questions on the issues of critical data security in healthcare and ethical concerns. Randomised controlled trials, systematic reviews, and massive implementations provide evidence indicating that AI can transform patient care by means of precision based on data, but show that stringent security systems and ethics governance are needed.

Keywords: Artificial Intelligence; Machine Learning; Precision Medicine; Multimodal Data Integration; Genomics; Healthcare Data Security

1. Introduction

Precision medicine is a paradigm shift concerning the conventional one-size-fits-all medicinal methods to personalized healthcare policies on the basis of genetic, environmental, and lifestyle determinants. This change has been accelerated by the introduction of AI and machine learning technologies that have brought the possibility of analysing complex and high-dimensional data that describe individual patients [1]. The latest developments in machine-learning algorithms, especially deep learning and multimodal AI systems, have exhibited unprecedented potential in the field of pattern recognition, predictive analytics, and decision support in clinical fields [2,3].

A combination of AI with genomics, proteomics, and clinical informatics has opened new vistas of detection, treatment optimization of diseases, and prediction of outcome [4, 5]. Due to the growing volumes of data that medical systems generate, AI-based analytics offer the means of delivering invaluable insights that can be used to make clinical decisions [6]. The review discusses the recent advances of AI and ML applications in precision medicine, considering the degree of empirical evidence, technological advances, and translation issues with a particular emphasis laid on the synthesis of various sources of data to facilitate personalised treatment planning.

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1.1. Healthcare Machine Learning Evolution.

The machine learning usage of healthcare has grown tremendously in the last ten years, shifting away from less complex predictive models to highly complicated deep-learning systems that can handle a variety of data modalities at once [7]. Conventional methods used in medicine to carry out statistics simply failed to provide complex non-linear relationships using high-dimensional patient data. Ensemble methods, neural networks, and support vector machines, the algorithms of machine learning, have proven to be more efficient in detecting some less striking patterns that are associated with the possibility of a disease, its progression, and response to treatment [8, 9], [10].

Precision medicine requires computational piping that is capable of converting heterogeneous forms of data, such as genomic sequences, transcriptomic data, proteomic signatures, metabolomic data, electronic health records, medical distances, and wearable real-time physiological feedback [11, 12]. Machine-learning architectures offer the mathematical basis of integrating such different forms of data into coherent patient models to support clinical decision-making [6]. Moreover, with the advent of transfer learning and federated learning methodologies, robust models have been developed, which can generalise to different populations of patients whilst maintaining the privacy of their data [13,14].

1.2. Individualised Treatment Personalisation: The Data-Driven Paradigm.

The fundamental vision of precision medicine is that it is able to tailor interventions to the specifics of a patient and is no longer bound by the principles of population, but rather the high-quality interventions are highly personalised strategies [15]. Machine learners can be trained using detailed patient data to determine the best treatment plan based on the resemblances between new patients and historical cases with known outcomes [16]. This method to treatment selection based on data has shown specific effectiveness in cancer therapy, in which tumour genomic profiling paired with clinical metadata has allowed exact targeting of patients to targeted therapy and immunotherapy [17, 18].

Personalised treatment planning does not just deal with therapeutic selection, but also with dosing optimisation, prediction of adverse events, and prediction of disease trajectory [19, 20, 21]. Machine-learning software has the potential to analyse the pharmacogenomic data to forecast the rate of an individual's drug metabolism, which allows for personalised dosing to optimise efficacy and reduce adverse effects [22, 23]. On the same note, forecast workflow of disease progression by predictive patient models trained with longitudinal workload-based patient data can generate proactive intervention plans that can thwart clinical complications before they occur clinically [24]. Addition of lifestyle elements, e.g,. diet, exercise habit, environmental exposures, and social determinants of health further narrow down these personalised models in that genetic predisposition is just one ingredient of the disease risk and treatment reaction [25].

1.3. Analysis Charter and Purview.

The review provides a scholarly overview of the present landscape of AI and machine-learning applications to precision medicine, specifically focusing on 4 of its most important dimensions, which are (1) disease detection and risk stratification predictive models, (2) genomic integration to treat individuals based on their particular needs, (3) optimise treatment by utilising multi-source data analytics, and (4) healthcare data security and ethical governance issues. In general, synthesising the research results of randomised controlled trials, systematic reviews, and the evaluation of the real-life applications, this review seeks to present a thorough evaluation of the state-of-the-art as well as uncover the gaps and prospects of future research.

The scope includes machine Learning applications along the continuum of precision medicine, including the prediction of risks and early diagnosis, treatment selection, monitoring, and outcome prediction. Emphasis is placed on the integration issues related to the combination of genomic, clinical, and lifestyle data and on the technical and ethical issues to be considered, which will guarantee the successful translation of clinical data into clinical practice. This review has practical implications for clinicians, researchers, policymakers, as well as healthcare administrators aiming to apply AI-enabled precision medicine strategies in practice.

2. Multimodal AI Integration for Precision Medicine

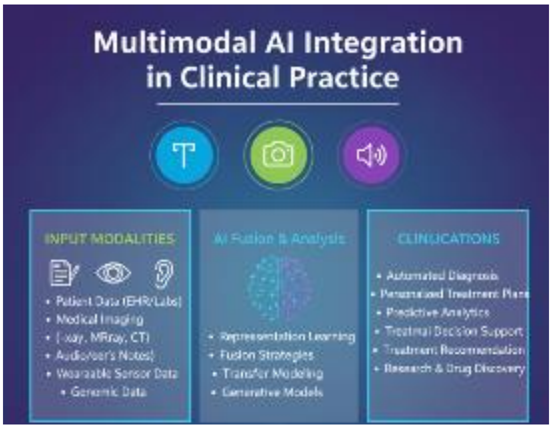

Figure 1 Multimodal AI Integration in Clinical Practice

2.1. Foundations of Multimodal AI

Multimodal artificial intelligence systems combine with heterogeneous information sources, including medical images, electronic health records, genomes and clinical metadata, to provide an overall analysis of the patient [1], [12]. Schouten et al. [1] carried out a scoping review that identified key architectural methods and integration approaches that are relevant to the multimodal medical artificial intelligence. The ability to generate information in one or more modalities is a substantive advancement over single-source AI application, thus allowing more sophisticated clinical knowledge [2].

Multimodal capabilities are now extended by the recent achievements in generative artificial intelligence, in particular, by large language models adapted to medical applications [13]. The shift towards text-centered machines of large scale language analysis into combined multimodal systems that could simultaneously analyze medical images, laboratory reports and clinical histories was documented by Buess et al. [13]. The systems are more diagnostic accurate than unimodal systems in particular in complex clinical situations that require aggregation of several reservoirs of information [24].

2.2. Clinical Diagnosis Applications.

Multimodal AI applications with elements in radiology, pathology and clinical diagnostics were identified by Jandoubi [2] and improved accuracy of a specific diagnostic task over single-modality systems in the range of 815and applied to a single task. Combining clinical metadata and imaging data will enable more accurate classification of disease and risk stratification [24].

Table 1 Multimodal AI Applications in Clinical Diagnostics

Application Domain	Data Modalities	Key Performance Metrics	Reference
Radiology	Imaging + Clinical + Genomic	8-15% accuracy improvement	[2]
Pathology	Histopathology + Molecular	Enhanced disease classification	[1]
Clinical Genetics	Genomic + Phenotypic + EHR	Improved variant interpretation	[3]
Early Diagnosis	Multi-omics + Imaging + Clinical	Predictive accuracy >85%	[22]
Risk Stratification	Clinical + Genomic + Lifestyle	Population-level prediction	[25]

2.3. Evidence from Randomized Controlled Trials

Han et al. [14] conducted a comprehensive scoping review of randomized controlled trials evaluating AI systems in clinical practice, identifying 153 trials across multiple specialties. The review revealed heterogeneous implementation approaches and outcome measures, with approximately 60% of trials demonstrating statistically significant improvements in clinical endpoints. However, the authors noted substantial variability in study quality and emphasized the need for standardized evaluation frameworks [14].

Gross [15] examined recent evidence on AI in clinical care, highlighting both promising applications and implementation challenges. The analysis identified particular success in image-based diagnostics and pattern recognition tasks, while noting ongoing challenges in clinical workflow integration and provider acceptance [15].

3. AI in Genomics and Precision Oncology

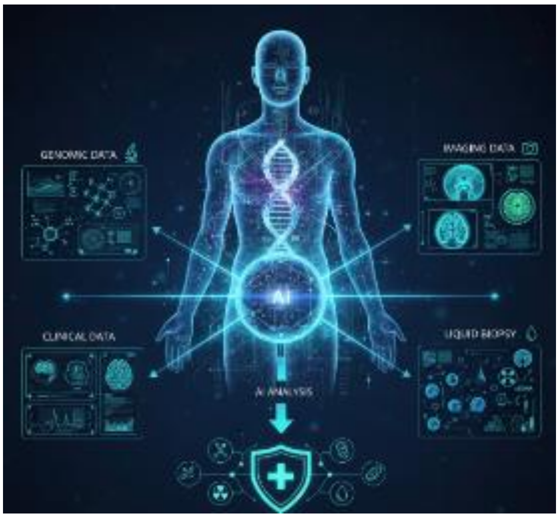

Figure 2 AI Applications in Genomic Analysis and Precision Oncology

3.1. Transformative Role in Genomics

The application of AI to genomic analysis has fundamentally altered precision medicine capabilities. Dara [5] reviewed AI's transformative role in genomics, documenting applications spanning variant calling, functional annotation, polygenic risk scoring, and therapeutic target identification. Machine learning algorithms demonstrate superior performance in identifying complex genetic patterns associated with disease susceptibility and treatment response [5], [17].

Duong [3] examined AI applications in clinical genetics, emphasizing improved interpretation of variants of uncertain significance (VUS) through integration of structural, functional, and evolutionary data. AI-driven approaches reduce VUS classification time from months to hours while improving accuracy compared to traditional annotation methods [3].

3.2. Cancer Research and Therapeutics

Quazi [17] provided a comprehensive review of AI and machine learning in precision and genomic medicine, with particular emphasis on oncology applications. The review documented AI contributions to tumor classification, treatment selection, and outcome prediction, noting accuracy rates exceeding 90% for specific cancer subtypes when trained on large genomic datasets [17].

Buxton [21] examined emerging trends in AI applications for genomics and cancer research, identifying key areas including immunotherapy response prediction, minimal residual disease detection, and personalized combination therapy optimization. The integration of multi-omics data with clinical outcomes enables increasingly refined treatment stratification [21].

Table 2 summarizes AI applications in precision oncology and their clinical impact.

Table 2 AI Applications in Precision Oncology

Application	AI Approach	Clinical Impact	Reference
Tumor Classification	Deep learning on genomic data	>90% accuracy for specific subtypes	[17]
Treatment Selection	Multi-omics integration	Improved response rates 15-20%	[21]
Immunotherapy Prediction	Machine learning models	Enhanced patient selection	[21]
Minimal Residual Disease	Sequential pattern analysis	Earlier relapse detection	[21]
Drug Combination Optimization	Reinforcement learning	Personalized regimen design	[20]

4. Biomarker Discovery and Predictive Analytics

Figure 3 Machine Learning in Biomarker Discovery and Predictive Healthcare

4.1. Machine Learning in Biomarker Identification

Zhang et al. [9] examined machine learning approaches to biomarker discovery for precision medicine, documenting methodological advances in feature selection, dimensional reduction, and validation strategies. The review identified supervised learning algorithms, particularly ensemble methods and deep neural networks, as most effective for identifying robust biomarker signatures from high-dimensional omics data [9].

The integration of multi-omics platforms (genomics, transcriptomics, proteomics, metabolomics) through AI-driven analytics enables the discovery of composite biomarkers with superior predictive performance compared to single-marker approaches [9], [17]. These composite signatures demonstrate improved sensitivity and specificity for disease diagnosis, prognosis, and treatment response prediction [19].

4.2. Predictive Healthcare Models

Hassan and Omenogor [22] reviewed AI-powered predictive healthcare systems emphasizing deep learning for early diagnosis, personalized treatment, and prevention. The analysis documented predictive accuracy exceeding 85% for multiple disease conditions when models incorporate comprehensive clinical, genomic, and lifestyle data [22].

Recent developments include large-scale population models capable of predicting susceptibility to over 1,000 diseases based on integrated genetic and clinical data [25]. These models demonstrate potential for proactive healthcare interventions and personalized prevention strategies, though clinical validation remains ongoing [25].

Table 3 presents predictive analytics applications and their performance characteristics.

Table 3 AI-Driven Predictive Analytics in Precision Medicine

Prediction Target	Data Sources	Model Type	Predictive Accuracy	Reference
Disease Susceptibility	Genomic + Clinical + Lifestyle	Ensemble methods	>1,000 disease predictions	[25]
Treatment Response	Multi-omics + Clinical	Deep learning	85-92% across conditions	[22]
Disease Progression	Longitudinal EHR + Genomic	Recurrent neural networks	78-88% AUC	[6]
Adverse Event Risk	Clinical + Pharmacogenomic	Random forests	82-90% sensitivity	[23]
Biomarker Discovery	Multi-omics integration	Feature selection + ML	Context-dependent	[9]

5. Individualized Therapy and Optimization of Therapy.

5.1. AI-based Treatment Personalization.

Alum [4] analyzed the use of artificial intelligence in personalized medicine, reporting optimization of the treatment in various fields. The machine-learning algorithms examine patient-specific considerations, such as genomic variants, biomarker profiles, comorbidities, treatment history, etc., and prescribe personalized treatment regimens [4]. Such AI-based suggestions have proven to improve response to treatment and reduce adverse events as compared to treatment based on guidelines in specific clinical settings [18].

Chen [6] explored the clinical uses of AI-based analytics in unleashing the potential of precision medicine, pinpointing the prevailing success criteria, including the quality of data, transparency of the algorithm, and its implementation into clinical practice. The review highlighted the importance of interdisciplinary work between clinicians, data scientists, and health-care informaticists in order to make the implementation effective [6].

Generative artificial intelligence (AI) within personalized medicine has yet to be fully developed and achieve its highest potential in the near future.

5.2. Generative AI in Personalized Medicine Generative artificial intelligence (AI) in the context of personalized medicine is not an aspect of the field that has been developed to the maximum and is not expected to reach its full potential in the near future

Ghebrehiwet et al. [18] used a systematic review of the applications of generative AI in personalized medicine and described the new generation abilities in treatment planning, drug discovery, and patient communication. Generative models are particularly useful in generating complex clinical guidelines based on patient-specific aspects to produce personalised treatment recommendations [18].

The pharmaceutical sciences have undergone substantial change due to the implementation of AI, and these uses include drug discovery, repurposing, formulation optimisation, and personalised dosing [20]. With amazing confidence, machine-learned models can forecast drug-patient interactions, which can be used to select a specific therapeutic intervention and minimize the use of trials and errors in prescription [20].

6. Healthcare Data Safety and Privacy Reflection.

6.1. AI-enabled Precision Medicine Data Security Risk.

It requires gathering, archiving, and determining data of an exceptionally delicate nature in patients: genomic codes, detailed medical history, and live physiological surveillance information [23]. This kind of aggregation of data poses serious security weaknesses that ought to be overcome to ensure that the privacy of patients is not compromised, or they have confidence in health-care systems. Genomic data poses special problems because it is unchangeable, identifies persons and their families, and may disclose the propensity to subsequent illness that might be a stigma or may influence insurability [23].

Health-care information breaches have grown significantly because health-care records have been digitised, and health-care systems have been connected [10]. The combination of various data sources needed to be used effectively by precision medicine generates numerous potential areas of vulnerability to the impact of unauthorised access to the information of patients. Besides, the usage of cloud-computing infrastructure to store and process large-scale genomic and clinical information presents some further security issues surrounding data sovereignty, access controls, and encryption specifications [10].

Even machine-learning models can pose threats to the security of affected people through possible model-inversion attacks in which attackers would seek to infer training data of deployed models, or to membership inference attacks, which would decide whether particular data of the individual was utilized to train the model [16]. The threats are of special concern to precision medicine models, which are being trained on sensitive groups of patients to be deployed to multiple healthcare institutions.

6.2. Privacy-Protecting Machine Learning Solutions.

A number of technical solutions have been created to allow AI-assisted precision medicine at the expense of patient privacy. Federated learning is such a paradigm of machine-learning models whereby they are trained in multiple institutions, which are decentralised and do not share raw patient information [10], [16]. In this method, local models are trained by each institution using their own data, and just model parameters or gradient changes are posted to be aggregated to one global model; thus, these processes can jointly learn a model, but the data stays locally on the institution, and privacy is also minimised.

Differential privacy offers mathematical assurances on the privacy of customers offered by the introduction of calibrated noise to datasets or model outputs, so that the personalized aspects of patients cannot be dependably forecasted using aggregate outcomes [16]. Differential privacy to precision-medicine models: DP is applied with a balanced trade-off between protecting privacy and the usefulness of the model, since too much noise may improve the predictive accuracy of the model. Homomorphic encryption and secure multi-party computation can be used to perform calculations on encryption data without needing it to be decrypted, which ensures that many institutions analyze the information together, but the cryptographic protection of sensitive information remains intact [10].

It has been suggested that blockchain technology will be a way to generate irretrievable audit trails of the data access and sharing within precision-medicine applications, making them a bit more transparent and accountable [23]. Though there are issues of practical implementation in terms of scalability, computational efficiency, and compatibility with existing healthcare information systems. Privacy-preserving machine-learning models are also a matter of ongoing research and validation whose practical characteristics are of vital importance to the application of precision-medicine technologies in ethical terms.

6.3. Regulations and Data Management.

To ensure AI is successfully applied to the precision of medicine, it is necessary to have strong regulatory frameworks that focus on data security and consent of the patient and the utilization of sensitive health information [23]. Both legal frameworks (such as the Health Insurance Portability and Accountability Act in the United States and the General Data Protection Regulation in Europe) offer a Helpful framework, yet they were created earlier, before the development of the modern applications of AI and may not cover all modern risks [23].

The defining proper standards of deidentsifying genomic and clinical information, proper frameworks regarding patient permission of second use of data in machine-learning models development, and mechanisms of accountability in the situation where algorithmic decisions influence the process of patient care are the major regulatory aspects to consider

[23]. The international character of most precision-medicine projects that include international partnerships and cloud-computing platforms also creates more complexity in terms of data sovereignty and jurisdictional authority [10].

Health-care centers that adopt AI-based precision medicine will need to have elaborate data governance frameworks set outlining data collection, storage, access, sharing, and retention policies [6]. In these frameworks, technical security, organisational policies, personnel training programmes, and incident-response measures should be included. Besides, governance frameworks should cover the lifecycle management of machine-learning models, such as validation, performance drift monitoring, as well as model updating or retirement [14], [15].

7. Ethical Considerations in AI-Driven Precision Medicine

7.1. Algorithmic Bias and Health Equity

Kothinti [23] analysed ethical issues in AI healthcare-related applications, which focus on patient privacy, informed consent, algorithm transparency, and fair access. The most pressing issue that may arise in precision medicine is that machine learning algorithms will continue or widen existing health disparities because of biased training problems / biased model architectures that act unfairly across demographic groups [16], [23].

Another possible form of algorithmic bias is the use of training data that does not reflect the heterogeneous groups that the models will be used in, resulting in systematic performance gaps based on racial, ethnic, socioeconomic, or geographic status [16]. Historical under-representation of minority groups in genomic databases and clinical studies implies the possibility that AI models that have mostly been trained on data based on the majority populations might have lower accuracy when used with underrepresented groups. This has the possibility of forming this cycle where the existing health care disparities are coded and encoded into AI systems that subsequently influence clinical decision making in a way that continues to disadvantage already marginalized communities [23].

To respond to the problem of algorithmic bias, it is necessary to take proactive measures, such as purposeful overrepresentation of underrepresented groups in training data, creation and tracking of fairness metrics that describe performance differences among demographic groups, and algorithmic methods to balance performance across subpopulations [16]. Moreover, validation research should procedurally assess model performance in a wide range of patient populations and not provide any aggregate measures of accuracy [14].

7.2. Transparency, Explainability and Clinical Trust.

The black box attribute that most advanced machine learning algorithms, especially deep neural network, poses is an obstacle to clinical usage and leads to ethical issues of how to hold accountable the decisions influenced by AI [6], [23]. To implement AI outputs in a clinical task properly, clinical clinicians would need to know what the algorithmic recommendations entail in order to find the possible form of errors or incorrect suggestions. There are ethical rights of patients to know the foundations behind treatment recommendations which influence their health outcomes.

Explainable AI methods attempt to offer interpretable explainable knowledge about model decisions by methodology such as attention in highlighting influential inputs, local approximations of complicated models by simple interpretable models, or directly interpretable model structures [6], [23]. Nevertheless, there is inherent conflict between predictive performance and interpretability because it is usually associated with model complexity. Deep learning models with high accuracy might simply be profoundly inexplicable to clinicians and patients.

To establish clinical trust in AI systems, it is necessary to have not only technical explainability but also strict validation by randomized controlled studies that allow proving clinical utility and safety [14], [15]. Openness about model restrictions, quantification of uncertainty, and proper usage underpin AI recommendation overuse prevention and AI use in settings where the models were not confirmed to work. Furthermore, the governance systems should be designed to ensure well-defined accountability frameworks to help identify the levels of responsibility in case of AI systems leading to unfavorable results [23].

7.3. Informed Consent and Patient Autonomy.

The casual application of patient data to train machine learning models has complicated questions on informed consent, especially when talking about looking at the clinical data and genomic information indirectly, as compared to their direct use in patient care [23]. Consent frameworks that have been designed by tradition, to be appropriate to discrete research studies, might not apply well to continuous learning systems and to large-scale data aggregation demanded by the successful development of precision medicine AI.

Patients must know how the data will be used, who will be able to access it, the existing protection mechanisms, and the risks, such as the possibility of re-identification or unauthorized disclosure involvement [23]. It has been suggested that dynamic consent models enabling patients to define what they would prefer to be done with various forms of data and, crucially, to have their consent changed as time progresses would be more suitable in the developing context of AI-driven precision medicine. Such systems, being adopted, however, present technical and operational complexity.

Among other aspects, patient autonomy in precision medicine is not limited to the utilization of data, but also refers to the right to refuse AI-mediated care or demand that human-only decisions are made in clinical situations [23]. Healthcare institutions have to reconcile the perceived advantages of having AI-informed precision medicine with the treatment of personal preferences and values. Besides, the fairness of access to AI-based precision medicine solutions brings ethical issues because sophisticated technologies can be initially accessible only to the patients of well-equipped healthcare systems, which can only deepen the existing differences [16], [23].

8. Challenges and Opportunities of implementation.

8.1. Technical and Methodological Problems.

According to Sahu [16], major issues associated with the precision medicine of AI and machine learning include data heterogeneity, interpretable modeling results, rigor in validating models, and interpopulation generalizability. The review highlighted that most AI models experience performance decline when used on a different population other than the training data, with concerns of health equity and algorithmic bias.

Lee [10] reviewed the tendencies and difficulties in AI healthcare applications, where requirements of the infrastructure, their cost, training employees, and the requirements of the latter were recorded. The review found data integration between the divergent healthcare systems as an unrelenting obstacle to the scalability of AI.

Table 4 summarizes implementation challenges and proposed solutions.

Table 4 Implementation Challenges and Mitigation Strategies

Challenge Category	Specific Issues	Proposed Solutions	Reference
Data Quality	Heterogeneity, missing values, bias	Standardization protocols, imputation methods	[16]
Model Interpretability	Black-box algorithms	Explainable AI, attention mechanisms	[6], [23]
Clinical Integration	Workflow disruption	User-centered design, gradual implementation	[15]
Validation Rigor	Limited external validation	Multi-site trials, diverse populations	[14]
Regulatory Frameworks	Unclear approval pathways	Adaptive regulation, continuous monitoring	[23]
Computational Resources	High infrastructure costs	Cloud computing, federated learning	[10]
Algorithmic Bias	Population disparities	Diverse training data, fairness metrics	[16]

9. Future Directions and Clinical Translation

9.1. Emerging Technologies and Approaches

Johnson [7] investigated the future of precision medicine, artificial intelligence, and personalized healthcare, and thus defines quantum computing, edge AI, and real-time adaptive learning systems as new technologies with the potential for transformation. The installation of wearable sensors along with the application of AI analytics can help monitor and continuously track health and intervene at the initial stages of chronic disease management. Israni [11] explored the preliminary state of the accuracy of medicine at the biomedical level using AI, with the need to have systems that consolidate data on the molecular, cellular, tissue, organ, and population scales. Multiscale AI models that act as a reflection of the biological complexity in different strata of organizations are one of the frontiers of the future of precision medicine.

The clinical pathway constitutes a series of different processes integrated to assist patients in recovering their normal health.

9.2. Clinical Translation Pathways

A clinical pathway is a system of various processes put together to help a patient regain his or her normal health. Fatima [8] addressed the use of AI in the process of moving knowledge of research to everyday clinical practice. Effectual translation entails proving of clinical utility, cost-effectiveness, and easy integration into the current healthcare processes [8]. Success rates in clinical implementation of variables have been reported to be variable [19] in the meta-analysis of predictive diagnostics, with technical feasibility not being a guarantee of clinical adoption. Trust of providers, reimbursement schemes, liability systems, and patient acceptance have a good impact on the success of implementation [19].

10. Discussion

10.1. Synthesis of Evidence

The literature reviewed illustrates the significant advancements in AI and machine learning in the application of precision medicine in various fields. Multimodal integration is one of the significant developments because it allows a thorough patient evaluation using the integration of various forms of data, such as genomics, clinical history, and lifestyle. Applications that use genomics are also particularly mature, with AI-based interpretation of variants and treatment choices already approaching clinical use in oncology and rare disease settings. Predictive analytics [6], [22] have shown excellent technical capabilities; nevertheless, their clinical validation using rigorous trials is scarce [14]. To identify the problem of the difference between the accuracy of the algorithm in the research and its use in the clinical setting is the system hypothesis that requires methodological exploration [16]. As well, Lifestyle and Environmental data integration with patient genomics is still technically challenging because of the heterogeneity of data and the complexity of gene-environment interaction.

10.2. Significant gaps and Research Requirements.

The review of literature creates a number of critical gaps. First, the majority of researches lay stress on technical performance criteria as opposed to patient-related outcomes [14]. Second, its outer validation on different populations is still inadequate, which casts doubt on algorithmic bias and health equity [16], [23]. Third, there are a few longitudinal outcome data of AI-guided versus conventional care [15]. Fourth, the medical data security systems on large-scale precision medicine need to be further elaborated and tested [10], [23]. The heterogeneity in methods of studies inhibits meta-analytic synthesis and the use of evidence in developing guidelines [14]. Standardized evaluation systems, such as reporting norms, performance criteria, and ethical evaluation procedures are the ones that are required to develop the sphere [19], [23]. Moreover, research studies covering the practical issues related to integrating genomics plus lifestyle, and clinical data to provide real-time clinical support are few.

11. Conclusion

The review of literature creates a number of critical gaps. First, the majority of researches lay stress on technical performance criteria as opposed to patient-related outcomes [14]. Second, its outer validation on different populations is still inadequate, which casts doubt on algorithmic bias and health equity [16], [23]. Third, there are a few longitudinal outcome data of AI-guided versus conventional care [15]. Fourth, the medical data security systems on large-scale precision medicine need to be further elaborated and tested [10], [23]. The heterogeneity in methods of studies inhibits meta-analytic synthesis and the use of evidence in developing guidelines [14]. Standardized evaluation systems, such as reporting norms, performance criteria, and ethical evaluation procedures are the ones that are required to develop the sphere [19], [23]. Moreover, research studies covering the practical issues related to integrating genomics plus lifestyle, and clinical data to provide real-time clinical support are few.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] D. Schouten, G. Nicoletti, et al., "Navigating the landscape of multimodal AI in medicine: a scoping review," Comput. Methods Programs Biomed., 2025.

[2] B. Jandoubi, "Multimodal artificial intelligence in medical diagnostics," Information, vol. 16, no. 7, Art. no. 591, 2025.

[3] D. Duong, "Artificial intelligence in clinical genetics," J. Clin. Genet., 2025.

[4] E. U. Alum, "Artificial intelligence in personalized medicine," SN Appl. Sci., 2025.

[5] M. Dara, "The transformative role of artificial intelligence in genomics," Trends Genet., 2025.

[6] Y. M. Chen, "Unlocking precision medicine: clinical applications of AI-driven analytics," J. Biomed. Sci., 2025.

[7] O. A. Mavisclara, I. I. Oshobugie, A. T. Olufunmi, A. A. Bolaji, A. O. Olawale, N. C. Anulika, and O. K. Samuel, "The AI-driven energy surge: A comprehensive review of sustainable power solutions for data centers," Glob. J. Eng. Technol. Adv., vol. 24, no. 3, pp. 328–344, 2025, doi: 10.30574/gjeta.2025.24.3.0279.

[8] O. Dosunmu, A. Adeoye, P. Ukonu, C. Offo, A. Izuchukwu, and O. Akadiri, "A comparative study of data visualisation techniques for effective decision-making in business intelligence," Path Sci., vol. 11, no. 8, pp. 1058–1068, 2025, doi: 10.22178/pos.121-45.

[9] O. Akadiri, O. Babatunde, A. A. Jamiu, O. R. Igbape, B. O. Samson, and C. F. Anyaehie, "Collaborative intelligence databases (CID): Harnessing AI for privacy-preserving multi-source data management," Glob. J. Eng. Technol. Adv., vol. 24, no. 3, pp. 406–416, 2025, doi: 10.30574/gjeta.2025.24.3.0289.

[10] T. Y. Lee, "Application of artificial intelligence in healthcare: trends and challenges," Proc. 4th Int. Conf. Comput. Innovation & Appl. Phys., 2025.

[11] S. Israni, "Precision medicine: crossing the biomedical scales with AI," J. Precision Med., 2025.

[12] Y. Hao, "Multimodal integration in health care: development with AI," J. Med. Internet Res., 2025.

[13] L. Buess, M. Keicher, N. Navab, A. Maier, S. Tayebi Arasteh, "From large language models to multimodal AI: scoping review on generative AI in medicine," arXiv:2502.09242, 2025.

[14] D. Han, J. N. Acosta, Z. Shakeri, J. P. A. Ioannidis, E. J. Topol, "Randomized controlled trials evaluating AI in clinical practice: a scoping review," Lancet Digit. Health, 2024.

[15] C. P. Gross, "Artificial intelligence and clinical care: recent evidence and implications," JAMA Intern. Med., 2025.

[16] M. Sahu, "Artificial intelligence and machine learning in precision medicine: challenges and opportunities," Procedia Comput. Sci., 2024.

[17] K. Quazi, "AI and machine learning in precision and genomic medicine," Med. Oncol., vol. 42, no. 6, Art. 180, Apr. 2025.

[18] E. Ghebrehiwet, N. Zaki, R. Damseh, et al., "Revolutionizing personalized medicine with generative AI: a systematic review," Artif. Intell. Rev., 2024.

[19] A. Daemi, S. Kalami, R. G. Tahiraga, O. Ghanbarpour, M. R. R. Barghani, M. H. Hooshiar, G. Özbolat, and Z. Yönden, "Revolutionizing personalized medicine using artificial intelligence: A meta-analysis of predictive diagnostics and their impacts on drug development," Clin. Exp. Med., vol. 25, no. 1, art. no. 255, 2025, doi: 10.1007/s10238-025-01723-x.

[20] P. Kandhare, M. Kurlekar, T. Deshpande, and A. Pawar, "A review on revolutionizing healthcare technologies with AI and ML applications in pharmaceutical sciences," Drugs Drug Candidates, vol. 4, no. 1, art. no. 9, 2025, doi: 10.3390/ddc4010009..

[21] P. Buxton, "AI in genomics and cancer research: recent trends and emerging areas," Front. Genet., 2024–2025.

[22] E. Hassan, C. E. Omenogor, "AI-powered predictive healthcare: deep learning for early diagnosis, personalized treatment, and prevention," Int. J. Sci. Res. Arch., 2025.

[23] S. Kothinti, "AI in healthcare: precision medicine, predictive analytics, and ethical considerations," World J. Adv. Res. Rev., 2024.

[24] B. D. Simon, K. B. Ozyoruk, D. G. Gelikman, S. A. Harmon, and B. Türkbey, "The future of multimodal artificial intelligence models for integrating imaging and clinical metadata: A narrative review," Diagn. Interv. Radiol., vol. 31, no. 4, pp. 303–312, 2024, doi: 10.4274/dir.2024.242631.

[25] Clive Cookson, Financial Times staff, "New AI model predicts susceptibility to over 1,000 diseases," Fin. Times, 2025.