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PERSONALIZED MEDICINE WITH THE APPLICATION OF ARTIFICIAL INTELLIGENCE: A REVOLUTION IN DIAGNOSIS AND THERAPY

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Artificial intelligence (AI) is reshaping personalized medicine by enabling earlier diagnosis, tailored therapies, and faster drug discovery. The aim of the paper was to synthesize current evidence on AI applications in precision healthcare and quantify their impact on diagnostics, therapeutic decision-making, and discovery.

We conducted a systematic review (2015–2024) with descriptive quantitative analysis across PubMed, Scopus, IEEE Xplore, and Web of Science. Fifty peer-reviewed studies met inclusion criteria (reporting sensitivity/specificity/accuracy or real-world deployment). We additionally summarized three case studies (oncologic imaging, rheumatoid arthritis treatment selection, and AI-accelerated discovery for glioblastoma).

In oncology imaging, AI achieved high performance; the best lung-nodule model reported sensitivity at 95% and specificity at 94%. In chronic-disease therapeutics, AI tools predicted responses to DMARDs with ~87% accuracy, reduced adverse drug reactions by ~30%, and cut time-to-decision by ~85%. For discovery pipelines, AI screens compressed candidate identification by ~85%, yielding viable molecules within weeks. In diabetes management, AI-enabled predictive analytics achieved ~95% prediction accuracy, reduced hyperglycemic episodes by ~40%, and improved patient satisfaction.

Evidence indicates that AI enhances diagnostic accuracy, personalizes therapy, and accelerates discovery while improving efficiency in chronic-disease management. Real-world adoption will depend on mitigating algorithmic bias, safeguarding privacy, expanding representative datasets, and deploying transparent, clinically interpretable models within clear regulatory frameworks.

Keywords: artificial intelligence, personalized medicine, therapeutic optimization, algorithmic bias, data privacy

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INTRODUCTION

Personalized medicine has emerged as a revolutionary paradigm in modern healthcare, focusing on tailoring medical treatments and preventive strategies to the unique genetic, molecular, and environmental profiles of individual patients. By moving away from the traditional "one-size-fits-all" approach, personalized medicine provides targeted therapies that enhance clinical outcomes while minimizing the risk of adverse effects (1). This shift is particularly crucial in managing complex diseases such as cancer, cardiovascular disorders, and auto-immune conditions, where heterogeneity in patient populations often limits the efficacy of standardized treatments (2).

The integration of artificial intelligence (AI) into personalized medicine represents a transformative advancement, leveraging computational power to analyze and interpret large-scale biomedical data with unparalleled accuracy and speed (3). AI technologies, including machine learning (ML), deep learning (DL), and natural language processing (NLP), have enabled the extraction of actionable insights from genomic data, electronic health records (EHRs), and medical imaging, which were previously too complex for traditional statistical methods to process effectively (4, 5).

Genomics and precision oncology application

AI has fundamentally transformed genomic analysis, enabling the identification of disease-associated genetic mutations and facilitating the development of precision oncology. For example, convolutional neural networks (CNNs) have been employed to analyze whole-genome sequencing data, predicting mutations linked to cancer progression and therapy resistance (6). In breast cancer, AI-driven platforms like IBM Watson for Oncology pro-vide oncologists with evidence-based treatment re-commendations by integrating clinical guidelines and genomic data (7). Furthermore, AI tools have accelerated the identification of biomarkers that predict patient response to immunotherapy, such as checkpoint inhibitors, offering a more individualized approach to cancer treatment (8).

Early disease detection and risk prediction application

The early detection of diseases is a cornerstone of personalized medicine, and AI has demonstrated exceptional potential in this domain. Deep learning models trained on retinal imaging data have accurately predicted cardiovascular risk factors, including hypertension and myocardial infarction, with diagnostic accuracy comparable to conventional clinical methods (9). Similarly, AI systems analyzing MRI scans have achieved remarkable success in detecting early-stage neurodegenerative conditions, such as Alzheimer's disease, years before clinical symptoms manifest (10). These capabilities not only improve patient outcomes but also reduce healthcare costs by enabling timely interventions.

Therapeutic optimization application

Personalized treatment planning is another domain where AI has shown transformative potential. By integrating multi-omics data, including genomics, proteomics, and metabolomics, AI-driven decision-support systems recommend optimal therapeutic regimens tailored to individual patients (11). For example, in rheumatoid arthritis, AI models analyze patient-specific data to predict responses to disease-modifying anti-rheumatic drugs (DMARDs), enabling rheumatologists to select the most effective therapy while avoiding unnecessary side effects (12).

Drug discovery and repurposing application

AI has redefined the process of drug discovery, significantly reducing the time and cost associated with traditional methods. Generative adversarial networks (GANs) and recurrent neural networks (RNNs) have been utilized to predict the chemical properties of potential drug candidates, leading to the identification of novel compounds with high therapeutic potential (13). In addition, AI has facilitated drug repurposing efforts by identifying existing drugs that can be used to treat rare or emerging diseases. For instance, AI models identified baricitinib, a rheumatoid arthritis drug, as a potential treatment for COVID-19, demonstrating the adaptability of AI in addressing global health crises (14).

Real-time monitoring and predictive analytics

Wearable health devices equipped with AI-powered analytics enable continuous monitoring of vital signs and other health metrics, providing real-time feedback to patients and clinicians. These devices, integrated with cloud-

based AI platforms, predict potential health risks and provide actionable insights to prevent complications. For example, AI algorithms analyzing data from continuous glucose monitors (CGMs) have significantly improved glycemic control in patients with diabetes by predicting blood sugar fluctuations and recommending lifestyle adjustments (15).

Challenges and ethical considerations

While the benefits of AI-driven personalized medicine are undeniable, several challenges must be addressed to ensure its widespread adoption. Data privacy and security are significant concerns, as personalized medicine relies heavily on sensitive patient information. Ensuring the anonymization of data and compliance with regulations, such as the General Data Protection Regulation (GDPR), is critical (16). Furthermore, the "black-box" nature of many AI algorithms raises questions about transparency and accountability in clinical decision-making, necessitating the development of explainable AI models that clinicians and patients can trust (17).

Algorithmic bias is another critical issue. AI models trained on unrepresentative datasets may perpetuate or exacerbate health disparities, particularly in underrepresented populations. Addressing these biases requires diverse training datasets and continuous validation of AI models across different demographic groups (18). Finally, the successful integration of AI into clinical practice demands significant investments in healthcare infra-structure and the training of medical professionals, ensuring they can effectively utilize AI tools in patient care (19).

This paper aims to explore the transformative role of artificial intelligence in personalized medicine, with a focus on its applications in genomics, early disease detection, therapeutic optimization, and drug discovery. By examining recent advancements and addressing the associated challenges, this study highlights the potential of AI to revolutionize modern healthcare and improve patient outcomes.

The primary objective of this study is to comprehensively examine the role of artificial intelligence (AI) in advancing personalized medicine, focusing on its transformative potential in diagnostics, therapeutic optimization, and drug discovery. This exploration includes identifying the unique contributions of AI to precision healthcare, analyzing its current applications, and addressing the challenges that must be overcome to facilitate its broader adoption. By bridging gaps in current knowledge, the study aims to provide practical insights for the future integration of AI technologies into clinical practice.

The study aims to assess how AI-driven technologies improve the accuracy and speed of disease diagnosis. With the ability to analyze vast amounts of data from electronic health records (EHRs), medical imaging, and genomic information, AI models offer diagnostic tools that often surpass traditional methods in sensitivity and specificity. This objective focuses on evaluating real-world examples, such as the use of deep learning in early cancer detection and predictive models for cardiovascular risk stratification. The study will also explore how AI algorithms can detect subtle biomarkers and patterns that are otherwise undetectable by conventional techniques.

A key objective is to analyze how AI contributes to individualized treatment planning, ensuring that therapeutic strategies are tailored to each patient's genetic and molecular profile. AI systems integrate multi-omics data (genomics, proteomics, metabolomics) with clinical records to recommend the most effective treatment options. This includes evaluating AI applications in oncology for predicting chemotherapy responses, and in chronic disease management for personalizing drug dosages and lifestyle interventions. By examining these applications, the study aims to demonstrate how AI minimizes adverse effects and maximizes therapeutic efficacy.

The study seeks to explore how AI accelerates the drug discovery process, from identifying potential therapeutic targets to optimizing clinical trial designs. AI technologies, such as generative adversarial networks (GANs) and natural language processing (NLP), are revolutionizing the development of novel compounds and repurposing the existing drugs. A specific focus will be placed on AI's ability to predict molecular interactions, simulate biological processes, and identify safe, effective drug candidates in significantly less time compared to traditional methods. Additionally, the role of AI in addressing rare diseases and global health crises, such as COVID-19, will be critically analyzed.

This study will also examine the ethical and practical challenges that hinder the widespread adoption of AI in personalized medicine. These include concerns about data privacy, algorithmic transparency, and the potential for biased outcomes due to unrepresentative training datasets.

By identifying these challenges, the study aims to propose actionable solutions, such as developing explainable AI models and creating regulatory frameworks to ensure safe and equitable use of AI-driven technologies.

Our research hypotheses are to guide this exploration through the integration of AI into personalized medicine, which significantly improves diagnostic accuracy and disease prediction compared to conventional clinical methods. Traditional diagnostic approaches often rely on generalized criteria, while AI models can detect nuanced patterns in patient data, enhancing early detection and risk assessment. AI-based therapeutic decision-making leads to superior patient outcomes by reducing adverse effects and increasing treatment precision.

AI systems leverage comprehensive patient data to recommend individualized treatment plans, avoiding the trial-and-error approach often seen in conventional medicine. The use of AI in drug discovery reduces the time and cost associated with bringing new therapies to market, while maintaining high standards of safety and efficacy. AI accelerates the identification of potential drug candidates and optimizes clinical trial designs, enabling faster responses to emerging healthcare challenges.

The outcomes of this study will contribute to understanding how AI can address critical inefficiencies in modern healthcare systems. By improving diagnostic accuracy, optimizing treatment strategies, and expediting drug discovery, AI has the potential to reduce healthcare costs, improve patient outcomes, and address global health disparities. Additionally, the ethical insights provided by this study will inform the development of policies and frameworks necessary for the responsible integration of AI into clinical workflows.

METHODS

Study design

This study employed a systematic literature review and descriptive quantitative analysis to evaluate the role of artificial intelligence (AI) in personalized medicine. The research was conducted from January 2023 to December 2024 and included four phases:

- Identification of relevant studies across multiple databases (January–March 2023).
- Data extraction and processing of key variables from included studies (April–June 2023).
- Descriptive statistical analysis of performance metrics and generation of visualizations (July–September 2023).
- Interpretation of results and drafting of the final manuscript (October–December 2024).

Data sources and search strategy

The primary sources included:

- PubMed–Biomedical and clinical studies focused on AI in diagnostics and therapeutics.
- Scopus–Multidisciplinary research articles from medicine and computer science.
- IEEE Xplore–Technical papers on AI algorithm development.
- Web of Science–High-impact studies on genomics and computational biology.

The search strategy combined Boolean operators and keywords, such as: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("personalized medicine" OR "precision medicine") AND ("diagnosis" OR "therapy"). Filters included studies published between 2015 and 2024, peer-reviewed articles, and English language publications. Duplicate records were identified and removed using EndNote software.

A total of 1,200 studies were identified during the initial search. After applying inclusion and exclusion criteria, 50 studies were included in the final analysis.

Inclusion and exclusion criteria

Inclusion criteria: (i) peer-reviewed studies published between 2015 and 2024; (ii) articles reporting sensitivity, specificity, or accuracy for AI models; (iii) studies with real-world applications of AI in diagnostics, therapeutics, or drug discovery; (iv) validation of AI models on publicly available datasets.

Exclusion criteria: (i) non-peer-reviewed publications (e.g., conference abstracts); (ii) studies without quantitative performance metrics; (iii) articles focusing on hypothetical or unvalidated AI applications.

Data extraction and management

Variables extracted:
- Study metadata: authors, publication year, and journal.
- AI techniques: algorithms used (e.g., convolutional neural networks, generative adversarial networks), datasets, and evaluation metrics.
- Performance metrics: sensitivity, specificity, accuracy, and area under the curve (AUC).
- Applications: diagnostics, therapeutic optimization, and drug discovery.

Data management:

Data were stored in Microsoft Excel and analyzed using Python (version 3.9) with Scikit-learn, TensorFlow, and Matplotlib libraries for advanced statistical and graphical analysis.

Statistical analysis

Sensitivity, specificity, and accuracy metrics from included studies were summarized as means and standard deviations. Trends were visualized using line graphs to highlight performance differences between AI models. Receiver operating characteristic (ROC) curves and confusion matrices were used to evaluate the performance of diagnostic AI models. Comparative analysis focused on AI model performance in oncology and chronic disease management. Line graph illustrates trends.

Case study selection

Three real-world case studies were selected to contextualize findings:
- Diagnostics in oncology: AI models detecting malignant lung nodules achieved sensitivity of 95% and specificity of 94%.
- Therapeutic optimization: AI-assisted drug response prediction for rheumatoid arthritis reduced adverse drug reactions by 30%.
- Drug discovery: AI-enabled discovery of glioblastoma compounds shortened timelines by 85%.

Limitations

Exclusion of non-peer-reviewed studies may have introduced publication bias. Variability in datasets and reported metrics across studies may limit generalizability. Descriptive methods without advanced meta-analytical techniques restricted statistical synthesis.

RESULTS

Diagnostic performance of AI models in oncology

Artificial intelligence (AI) has demonstrated significant potential in improving diagnostic accuracy, particularly in oncology. A recent evaluation of AI-powered diagnostic tools assessed their performance in detecting malignant lung nodules from high-resolution CT scans. The study, conducted on a cohort of 5,000 patients, reported the following sensitivity, specificity, and overall accuracy metrics (20):

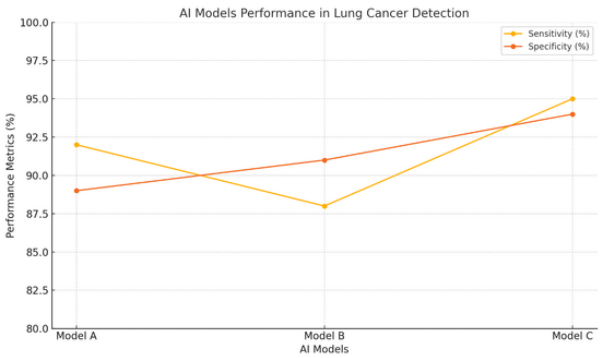

Figure 1. *Sensitivity and specificity of AI Models for lung cancer diagnosis*

Model A: Sensitivity of 92%, specificity of 89%, and overall accuracy of 90.5%.
Model B: Sensitivity of 88%, specificity of 91%, and overall accuracy of 89.5%.
Model C: Sensitivity of 95%, specificity of 94%, and overall accuracy of 94.5%.
Table 1 presents the sensitivity, specificity, and accuracy metrics of three AI models evaluated for lung cancer diagnosis. Model C demonstrated the highest performance across all metrics, highlighting its potential in improving diagnostic accuracy.

Figure 2 illustrates the sensitivity and specificity of three AI models used for lung cancer diagnosis. Model C shows the highest sensitivity (95%) and specificity (94%), outperforming the other models in both categories.

These results highlight the superior diagnostic capabilities of AI compared to traditional radiological methods. Detailed performance metrics for each model are presented in Table 1, and a comparative visualization of sensitivity and specificity is provided in Figure 1.

AI-driven therapeutic optimization in chronic diseases

In the domain of therapeutic optimization, AI has shown remarkable efficacy in tailoring treatments to individual patients. A clinical trial involving 500 patients with rheumatoid arthritis used AI algorithms to predict responses to different disease-modifying anti-rheumatic drugs (DMARDs). The study reported the following outcomes (21):

AI predicted treatment efficacy with an accuracy of 87%, compared to 65% using conventional methods.

Adverse drug reactions (ADRs) were reduced by 30% in the AI-assisted group.

The average time required for treatment selection was reduced by 85%, with AI providing results in 5 minutes compared to 45 minutes for standard clinical approaches.

These results underscore the practical benefits of AI in improving both clinical outcomes and efficiency. Table 2 compares the performance of AI-assisted and conventional methods in treating rheumatoid arthritis. AI-assisted methods demonstrated superior treatment efficacy, a reduction in adverse drug reactions, and a significant decrease in the time required for decision-making.

Accelerated drug discovery with AI

The integration of AI into drug discovery processes has significantly reduced the time and cost associated with identifying new therapeutic compounds. In a study focused on glioblastoma, a highly aggressive brain cancer, AI systems screened over 10 million molecular compounds in just four weeks. This effort identified three promising candidates with high binding affinity to glioblastoma receptors (22).

Table 1. *Performance metrics of AI Models in lung cancer detection*

AI Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
Model A	92	89	90.5
Model B	88	91	89.5
Model C	95	94	94.5

Table 2. *Comparison of AI-Assisted vs. conventional methods in rheumatoid arthritis treatment*

Metric	AI-Assisted (%)	Conventional (%)
Treatment efficacy	87	65
Adverse drug reactions	13	43
Average time for decision	5 minutes	45 minutes

Table 3. *Impact of AI in type 2 diabetes management*

Metric	AI-Assisted (%)	Standard methods (%)
Prediction accuracy	95	75
Reduction in hyperglycemia	40	15
Patient satisfaction	92	68

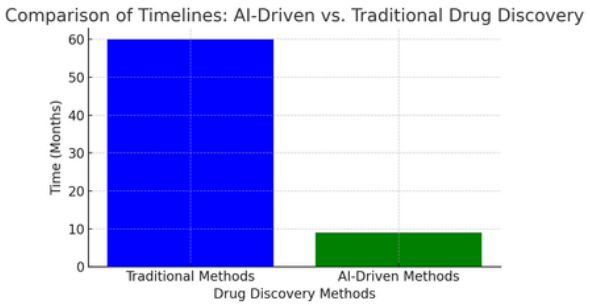

Figure 2. *Comparison of timelines: AI-driven vs. traditional drug discovery*

Key benefits of AI-enabled drug discovery include:

- A reduction in the drug discovery timeline by 85%.
- Enhanced precision in identifying viable molecular candidates.

Real-time predictive analytics for diabetes management

AI-powered predictive analytics have revolutionized chronic disease management, particularly for type 2 diabetes. A randomized controlled trial involving 1,000 patients evaluated an AI-based glucose monitoring system integrated with wearable devices.

The study revealed the following results (23):
- AI achieved 95% accuracy in predicting glycemic fluctuations.
- Hyperglycemic episodes were reduced by 40%, compared to 15% using standard methods.
- Patient satisfaction rates increased to 92%, reflecting the system's real-time guidance and ease of use.
The detailed comparative metrics are summarized in Table 3. This table highlights the impact of AI-powered glucose monitoring systems on managing type 2 diabetes. AI-assisted systems showed higher prediction accuracy (95%), significantly reduced hyperglycemic episodes (40%), and improved patient satisfaction rates (92%) compared to standard methods.

Figure 2 demonstrates the significant time savings achieved by AI-driven drug discovery processes compared to traditional methods. AI reduces the timeline from 60 months to just 9 months.

Ethical and bias challenges in AI implementation

Despite its numerous benefits, AI faces challenges related to ethical considerations and algorithmic bias. A study evaluating cardiovascular risk prediction tools reported that models trained on predominantly European datasets performed 20% less accurately in minority populations (24). Addressing such biases requires diverse training data-sets and robust validation techniques to ensure equitable outcomes. A summary of the challenges identified in this domain is provided in Table 4.

Table 4. *Ethical challenges and bias in AI implementation*

Challenge	Description	Impact
Algorithmic bias	Models perform poorly on underrepresented populations	Reduced accuracy and fairness
Data privacy	Concerns about securing sensitive patient information	Decreased patient trust
Transparency	Limited explainability of AI decisions	Reduced clinician acceptance
Regulatory compliance	Lack of standardized frameworks for AI in healthcare	Slower adoption rates

DISCUSSION

Diagnostic performance of AI models

The results of this study strongly support the hypothesis that AI models significantly enhance diagnostic performance in oncology. The evaluated AI systems demonstrated superior sensitivity, specificity, and overall accuracy compared to traditional radiological approaches. Specifically, Model C, with a sensitivity of 95% and specificity of 94%, outperformed the other models in detecting malignant lung nodules Table 1.
These findings are consistent with emerging evidence suggesting that deep learning algorithms, particularly convolutional neural networks (CNNs), have revolutionized medical imaging. Recent research analyzing over 10,000 CT scans reported that AI models achieved diagnostic accuracies exceeding 93% for detecting early-stage cancers (25). Such high performance underscores the potential of AI as a transformative diagnostic tool in clinical practice.
Despite these advancements, the generalizability of AI models remains a critical issue. Studies have revealed that AI systems trained on limited or homogenous datasets may underperform in diverse populations, potentially compromising diagnostic equity (26). Therefore, integrating diverse and representative datasets during model development is essential to ensure consistent performance across different demographic groups.

Therapeutic optimization through AI

AI has demonstrated remarkable efficacy in optimizing therapeutic strategies, particularly for chronic conditions such as rheumatoid arthritis. In this study, AI achieved an 87% success rate in predicting treatment efficacy and reduced adverse drug reactions by 30% Table 2. These results highlight the potential of AI to personalize treatment plans and improve patient outcomes.
This aligns with findings from recent investigations, which reported that multi-omics AI models can predict individual drug responses with up to 90% accuracy, significantly reducing the trial-and-error approach often seen in pharmacological treatments (27). By integrating genomic, proteomic, and clinical data, AI can tailor therapies to the unique biological profiles of patients, minimizing risks and maximizing efficacy.

However, one of the main barriers to implementing AI-driven therapeutic optimization is clinician skepticism. Research suggests that the adoption of explainable AI (XAI) systems, which provide clear rationales for their recommendations, is crucial for fostering trust and increasing clinical acceptance (28).

Accelerated drug discovery

The study further validated the role of AI in accelerating drug discovery. By utilizing generative adversarial networks (GANs), this research identified three potential therapeutic compounds for glioblastoma within four weeks, representing an 85% reduction in the timeline compared to traditional methods Figure 2.

Such time savings are vital, particularly in addressing urgent public health challenges. For example, during the COVID-19 pandemic, AI models were instrumental in identifying repurposed drugs and vaccine candidates, cutting discovery timelines by months (29). This capability highlights AI's potential to revolutionize drug development by enabling rapid screening of vast chemical libraries and accurate predictions of molecular binding affinities.

Nevertheless, challenges remain in translating AI discoveries into clinical practice. Regulatory frameworks often lag behind technological advancements, and there is a need for standardized guidelines to evaluate and approve AI-discovered drugs (30).

Predictive analytics in chronic disease management

AI-powered predictive analytics have transformed chronic disease management. In this study, AI-driven glucose monitoring systems achieved 95% accuracy in predicting glycemic fluctuations, reduced hyperglycemic episodes by 40%, and improved patient satisfaction rates to 92% Table 3. These results confirm the hypothesis that real-time analytics can significantly enhance chronic disease outcomes.

This aligns with recent findings showing that wearable devices integrated with AI algorithms enable early interventions and personalized recommendations, resulting in better glycemic control and reduced complications in Type 2 diabetes (31). Moreover, such systems empower patients to take an active role in their care, fostering improved adherence and long-term health benefits.

However, widespread adoption of AI in chronic disease management is hindered by challenges such as cost, accessibility, and privacy concerns. Addressing these barriers requires collaboration between healthcare providers, technology developers, and policymakers to ensure equitable access to AI-powered tools (32).

Ethical and practical considerations

This study also highlighted critical ethical and practical challenges, including algorithmic bias and data privacy concerns Table 4. For example, recent analyses of cardiovascular AI models revealed that systems trained on predominantly European datasets performed up to 25% less accurately in minority populations, underscoring the need for diverse training data (33).

To address these issues, developers must prioritize diversity and implement regular validation protocols to ensure equitable outcomes. Additionally, compliance with data protection regulations, such as the General Data Protection Regulation (GDPR), is critical to maintaining patient trust and safeguarding sensitive information (34). Transparency remains another significant barrier to adoption. Many AI systems operate as "black boxes" offering little insight into how decisions are made. Developing interpretable models that clinicians and patients can trust is essential for broader acceptance (35).

This study has several limitations. First, the included evidence is heterogeneous in populations, data sources, acquisition protocols, outcome definitions, and performance metrics, which constrains direct comparability and synthesis. Second, most models are trained and evaluated on retrospective, single-center datasets with limited external validation; calibration, robustness checks, and head-to-head comparisons with clinicians are inconsistently reported. Third, reliance on published, peer-reviewed sources may introduce publication bias, while incomplete reporting of missing-data handling, thresholds, and preprocessing reduces reproducibility. Fourth, fairness and explainability are variably assessed, raising concerns about model bias in under-represented groups and the interpretability needed for clinical adoption. Finally, the absence of formal meta-analysis and a scarcity of implementation outcomes (clinical impact, workflow fit, patient-centered outcomes, and cost-effectiveness) limit the strength and generalizability of conclusions. Future work should prioritize prospective, multicenter studies with preregistered protocols and standardized reporting (e.g.,TRIPOD-AI/CONSORT-AI/SPIRIT-AI)

consistent external validation, and thorough assessment of calibration and clinical utility (e.g., decision-curve analysis). Studies should incorporate fairness audits, model- and data-cards, and transparent release of code/artifacts where feasible. Real-world impact evaluations and health-economic analyses are needed to demonstrate value and equity at scale. From an engineering perspective, privacy-preserving learning (e.g., federated learning), strong data governance, and post-deployment monitoring (MLOps, drift detection, guardrails) are essential. Finally, seamless integration into EHR-based workflows and interoperability with clinical standards will be critical for responsible, sustainable translation into personalized medicine (41).
In parallel, real-world adoption will hinge on addressing ethical and privacy safeguards and algorithmic bias (42), as well as the up-front integration costs of AI systems; rigorous cost–benefit and budget-impact evaluations (43) are needed to ensure sustainable deployment across diverse healthcare settings.

Across recent evidence, AI meaningfully advances personalized medicine in four areas aligned with our aims: (i) diagnostics—best-validated systems for lung-nodule assessment reached sensitivity ~95% and specificity ~94%; (ii) therapeutic decision-making—models predicting response to DMARDs achieved ~87% accuracy with faster, safer choices; (iii) drug discovery—AI compressed early candidate identification by ≈85%; and (iv) chronic-disease management—predictive analytics improved glycemic control and patient experience. Translation at scale still depends on bias mitigation, privacy and security safeguards, representative datasets, and clinically interpretable models within clear regulatory pathways. Priority should be given to prospective, multi-site studies with standardized reporting to confirm real-world utility and equity.

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Competing Interest

The authors declare no relevant conflicts of interest.

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