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PHARMACOLOGY AND ARTIFICIAL INTELLIGENCE

Artificial intelligence for precision medicine

Marie-Elise Martel[a,b], **Adan José-Garcia**[a,c], **Celine Vens**[d,e], **Maarten De Vos**[f], **Vincent Sobanski**[a,b,g,*]

[a] *U1286 — Infinite — Institute for Translational Research in Inflammation, Inserm, Université de Lille, CHU de Lille, 59000 Lille, France*
[b] *Département de médecine interne et immunologie clinique, centre de référence des maladies auto-immunes systémiques rares du nord et nord-ouest, Méditerranée et Guadeloupe (CeRAINOM), CHU de Lille, 59000 Lille, France*
[c] *CNRS, centrale Lille, UMR 9189 CRIStAL, Université de Lille, 59000 Lille, France*
[d] *Department of Public Health and Primary Care, KU Leuven, 8500 Kortrijk, Belgium*
[e] *Itec, imec research group at KU Leuven, 8500 Kortrijk, Belgium*
[f] *Stadius Center for Dynamical Systems, Signal Processing and Data Analytics, Department of Electrical Engineering (ESAT), & Woman and Child, Department of Development and Regeneration, KU Leuven, 3000 Leuven, Belgium*
[g] *Institut universitaire de France (IUF), 75000 Paris, France*

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Summary

Introduction. — Precision medicine aims to tailor healthcare decisions and interventions to the unique biological and clinical characteristics of each patient. The recent convergence of artificial intelligence (AI) with advances in digital health, omics, and big data analytics has accelerated progress toward this goal. AI technologies — particularly machine learning, deep learning, natural language processing and generative large language models — enable the rapid and meaningful analysis of complex biomedical datasets, supporting more individualized care.

Purpose of review. — In this narrative review, we provide an accessible overview of the core principles of AI for healthcare professionals and explore its practical applications across the spectrum of precision medicine. Real-world examples highlight how AI is being used to enhance early diagnosis, guide treatment selection, support disease prevention, and even contribute directly to therapeutic interventions. Alongside these advances, we discuss critical limitations and challenges, including ethical considerations, algorithmic bias, data privacy concerns, environmental impact, and practical barriers to clinical implementation.

* Corresponding author. Department of Internal Medicine, Lille University Hospital, rue Michel-Polonowski, 59000 Lille, France.
E-mail address: vincent.sobanski@univ-lille.fr (V. Sobanski).

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Conclusion. — This review offers both an introduction to AI and a practical overview of how it is being used, and where its limitations lie, in precision medicine, with the goal of helping healthcare professionals understand these evolving tools and use them efficiently and responsibly in clinical practice.

Abbreviations

AI	artificial intelligence
ALL	acute lymphoblastic leukemia
AUC	area under the curve
CAL	coronary artery lesions
CNN	convolutional neural network
CT	computed tomography
CXR	chest X-ray
DL	deep learning
DT	digital twin
EHR	electronic health record
FKGL	Flesch-Kincaid Grade Level
GLLM	generative large language model
KD	Kawasaki disease
ML	machine learning
MRI	magnetic resonance imaging
NLP	natural language processing
P4	predictive, preventive, personalized, and participatory
RCT	randomized control trials
UC	ulcerative colitis

Introduction

Precision medicine, often used interchangeably with personalized or individualized medicine, is a transformative approach to tailor medical decisions, treatments, and interventions to the unique characteristics of each patient. In theory, this strategy incorporates non-modifiable (genome) and modifiable (environmental, lifestyle information) factors to guide more precise and effective healthcare. For the U.S. National Human Genome Research Institute, personalized medicine should leverage an individual's genetic profile to optimize therapeutic choices, dosing, and timing [1]. This comprehensive approach has advanced largely in parallel with developments in omics, artificial intelligence (AI), and digital health technologies. Among the most integrative frameworks of precision medicine is P4 medicine, which stands for ''predictive, preventive, personalized, and participatory''. P4 medicine emphasizes a data-rich and technology-driven approach to care, built upon the widespread availability of digital tools — - ranging from wearable devices and smartphones to high-throughput technologies and cloud computing [2,3]. These technologies enable the continuous collection, storage, and analysis of vast biomedical datasets (notably omics data). While the conceptual roots of personalized care are longstanding, what is novel today is the capacity to rapidly and meaningfully analyze these often large and complex datasets to inform real-time clinical decisions.

Central to this capability is AI. AI refers to systems capable of performing tasks that typically require human intelligence, such as pattern recognition, decision-making, or natural language understanding [4]. AI systems may be software-based (e.g., image recognition, predictive analytics) or embedded in hardware (e.g., smart devices, IoT applications). Key branches of AI used in healthcare include machine learning (ML), deep learning (DL), natural language processing (NLP) and generative large language models (GLLM). These technologies have already demonstrated powerful applications in genomics, biomarker discovery, medical imaging, and clinical decision support [5,6]. In clinical research and practice, AI has made it possible to uncover complex relationships within high-dimensional datasets — often unrecognizable by human analysis alone. These insights are increasingly used to personalize diagnosis, monitor disease progression, and select the most appropriate treatments for individual patients [7].

This narrative review explores the growing role of AI in precision medicine. We aim to describe the basis of AI, illustrate its current applications, thereby highlighting its strengths and limitations, and discuss its utility in bringing healthcare professionals closer to the longstanding goal of delivering the right treatment to the right patient at the right time.

Principles of artificial intelligence

The origins of AI date back to the 1950s, with early work by figures like Alan Turing, who proposed the Turing Test as a measure of machine intelligence [8]. Since then, AI has rapidly advanced, particularly with the advent of ML and DL. ML is a major subset of AI in which algorithms are able to learn patterns from data and make decisions or predictions without being explicitly programmed. DL takes it a step further as these models mainly utilize multiple layers of neural networks (inspired by the structure and function of

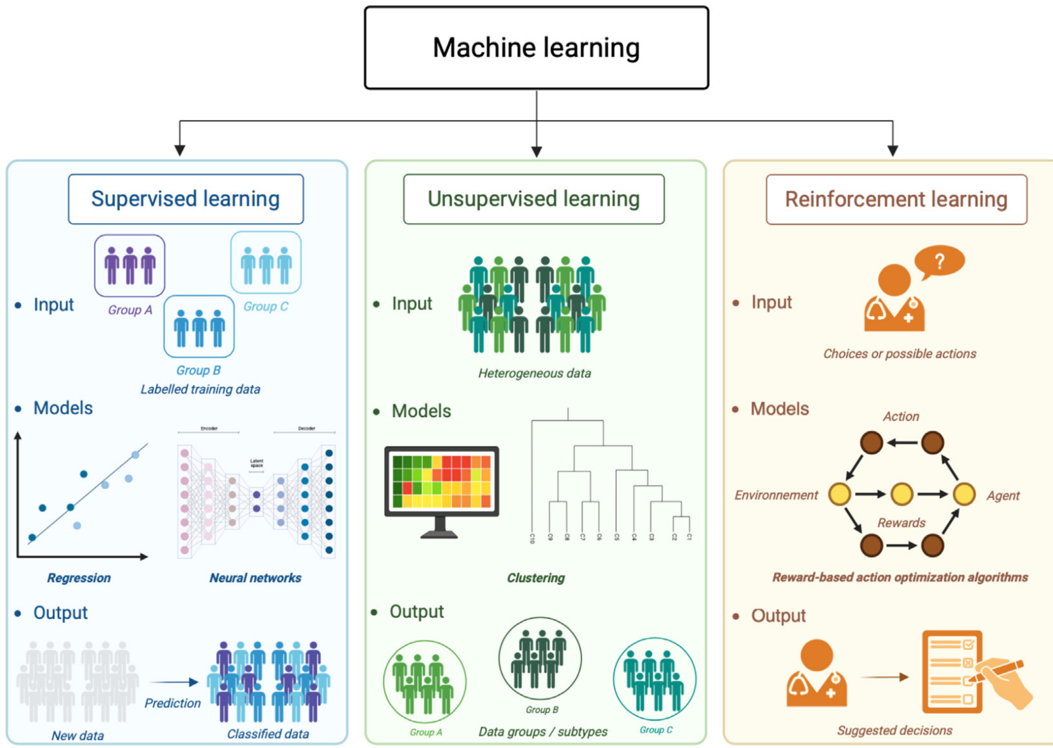

Figure 1. Overview of the three main types of machine learning: supervised, unsupervised, and reinforcement learning.

neurons in the human brain) to learn from large and complex datasets and process tasks such as image recognition and natural language understanding, allowing for breakthrough achievements in tasks like speech recognition, autonomous driving, and medical diagnostics. More recently, generative AI, and especially large language models (GLLMs) like GPT, has gained popularity. Trained on massive datasets composed of texts from various sources, these models learn statistical patterns in language to generate human-like text, answer questions, or translate languages, thanks to their ability to interpret and produce unstructured data [9].

AI methods are classified into three primary learning paradigms with very distinct objectives (Fig. 1): supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the model is trained on a labeled dataset where both input and output are known, enabling the system to predict outcomes based on this training. Unsupervised learning, on the other hand, works with unlabeled data, and is thus employed to uncover inherent patterns or structures within the data without predefined labels. It is therefore often preferred to perform grouping or clustering tasks. Reinforcement learning is an approach where a machine learns by trial-and-error, receiving rewards for actions that move it closer to a desired goal and penalties for actions that hinder progress, ultimately optimizing its behavior over time. To function effectively, AI systems follow a structured development pipeline (Fig. 2) that begins with data collection, where large volumes of relevant clinical or real-world health data are gathered. This is followed by data preprocessing, which involves cleaning, formatting, structuring and annotating the data to ensure quality and consistency, key features of the final model's results quality. During the model training phase, algorithms learn to recognize patterns and relationships within the data. Once trained, the model undergoes evaluation to assess its accuracy, robustness, and generalizability, often using separate validation datasets. Upon meeting performance criteria, the model is deployed into real-world clinical environments or applications. Importantly, when based on reinforcement learning algorithms, a feedback loop can enable an AI system to continuously refine their predictions and adapt over time by learning from new incoming data, enhancing both performance and relevance in dynamic healthcare settings. It is worth noting however that, despite the growing number of publications reporting well-evaluated models, relatively few are ultimately deployed in real-world clinical environments or applications.

Consequently, ML, but especially DL, often requires access to large volumes of high-quality data, which can be referred to as ''big data''. This data requirement is however not always essential and can be substantially reduced through transfer learning, a technique in which a model first trained on a large, general dataset is then adapted to perform a more specific task on an often much smaller and domain-oriented dataset. This data provides the foundation for training algorithms and as a result, beyond the quantity, it is more importantly the quality, accuracy, and representativeness of the data that are critical in determining how reliable and personalized the resulting insights will be (Box 1).

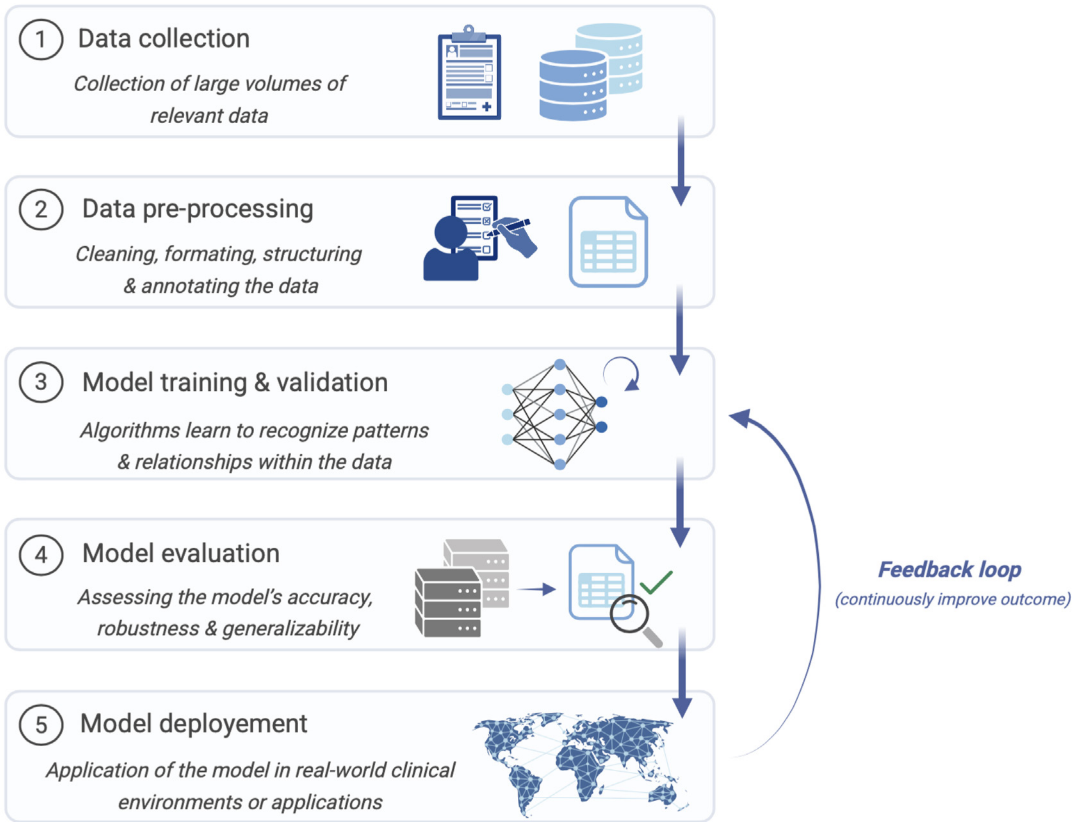

Figure 2. Stepwise workflow for artificial intelligence model development and implementation.

Box 1: Literature search and scope.
This narrative review was informed by a targeted search of key scientific databases including PubMed, Web of Science, and MedRxiv, focusing on recent and relevant articles related to AI applications in healthcare and precision medicine. While efforts were made to include a broad range of studies, this review is not systematic and therefore does not represent an exhaustive or comprehensive summary of all available literature. The selection reflects studies deemed most pertinent and illustrative examples of the themes discussed, aiming to provide healthcare professionals with a clear and practical overview of this topic.

Applications of AI in precision medicine

Diagnosis

Early diagnosis

In healthcare, early disease detection is often associated with improved prognosis. This relationship is particularly evident in oncology, where diagnosing cancer at an early stage significantly enhances survival rates. However, approximately 50% of cancers are still diagnosed at an advanced stage, mainly due to multiple challenges, including the limitations of current screening technologies and the difficulty in identifying lesions with malignant potential [10—12]. In this context, AI has emerged as a valuable tool to address these gaps (Table 1). Automated analysis of medical images and the integration of clinical data can provide critical diagnostic support. Convolutional neural networks (CNNs), for instance, have proven especially effective in detecting and classifying anomalies in imaging modalities such as radiography, CT scans, and MRI, achieving diagnostic accuracy comparable to that of experienced clinicians thus offering valuable support in the diagnostic process [13].

A recent extensive real-world study in Germany illustrated AI's potential in breast cancer screening. Eisemann et al. evaluated AI-supported double reading in mammography compared to standard double reading across more than 463,000 women [14]. Their results showed a 17.6% increase in cancer detection without raising the rate of women called back for additional assessment, along with improvements in the positive predictive values of both follow-up and biopsy.

Similarly, in dermatology, a DL algorithm trained on over 220,000 clinical images covering 174 skin disorders demonstrated high diagnostic accuracy in malignancy detection (AUCs of 0.937 and 0.928 on two independent datasets: SNU and Edinburgh) [15]. When clinicians used AI assistance, their sensitivity and F1 scores (Table 2) significantly improved, suggesting that AI can act as an effective augmented intelligence tool to support early skin cancer diagnosis.

Comparable approaches have been explored in many other fields, including early diagnosis of retinal diseases [16], cardiac arrhythmias [17,18], and sepsis [19]. In the latter, SepsisFinder — a machine-learned causal probabilis-

Table 1 Examples of artificial intelligence applications in personalized medicine and their key findings.

Applications of AI in personalized medicine		Key findings
Disease prevention		- AI platforms can predict and track infectious disease outbreaks early by analyzing global data sources, enabling proactive public health responses - AI-driven chatbots effectively promote healthier lifestyles and reduce cardiovascular and metabolic disease risks through personalized, behavior-focused interventions - Using predictive models from self-monitoring data, AI-generated personalized feedback supports effective daily management and prevention of chronic conditions like type 2 diabetes
Diagnosis	Early diagnosis	- AI-supported double reading using DL increased cancer detection without raising recall rates, outperforming standard radiologist-only double reading in both accuracy and efficiency - A DL algorithm trained on a large, diverse dermatological image dataset outperformed clinician assessments and significantly enhanced diagnostic sensitivity and precision when used as an assistive tool - An ML causal probabilistic model can identify sepsis up to 48 hours earlier than traditional scoring systems, offering superior predictive accuracy and earlier alerts based on routine EHR data
	Precision & differential diagnoses	- A multimodal AI model integrating clinical, cognitive, and imaging data distinguished between 10 dementia subtypes with high accuracy, outperforming standard clinical assessments and enhancing neurologists' diagnostic accuracy - ML classifiers effectively differentiated between overlapping neurological syndromes, offering superior precision over traditional clinical evaluations by detecting subtle, multidimensional patterns - ML models applied to routine clinical data achieved high sensitivity and specificity in distinguishing Kawasaki disease from other febrile illnesses and predicting coronary complications, improving diagnostic certainty in complex cases where standard methods are often ambiguous
	Disease progression prediction	- Boosting and random forest algorithms applied to clinical data predicted relapse and mortality in pediatric ALL with high accuracy, offering earlier and more individualized risk assessment than traditional prognostic tools - AI-assisted colonoscopy using real-time image analysis stratified UC patients by relapse risk during remission, enabling non-invasive, accurate prediction of flare-ups far beyond what standard endoscopic evaluation provides - Predictive models like XGBoost and simplified risk scores can be used to forecast renal flare risk post-remission in lupus nephritis, providing a data-driven foundation for personalized disease monitoring - A random survival forest model trained on a large MS registry predicted the timing of disability progression and provided interpretable outputs, equipping clinicians with transparent, patient-specific risk estimates to guide early intervention
	Prognosis	- An XGBoost model integrating clinical and blood test data predicted 5-year survival outcomes in non-small cell lung cancer with great accuracy, surpassing traditional staging systems in prognostic accuracy and aiding personalized postoperative planning - An AI-augmented model combining chest X-ray image analysis with clinical parameters outperformed standard tools like CURB-65 in predicting 30-day pneumonia mortality, demonstrating the value of integrating ML-derived imaging scores with conventional metrics
Treatment	Therapeutic target	- An AI platform integrating multi-omics data identified TNIK as a novel fibrosis target, enabling the development of a first-in-class inhibitor (INS018_055) that advanced to clinical trials - An AI-driven drug discovery pipeline identified non-traditional, conserved bacterial targets absent in humans, revealing novel antibiotic mechanisms

Table 1 (*Continued*)

Applications of AI in personalized medicine		Key findings
	Drug discovery & design	- DL models like AlphaFold predict protein 3D structures with high accuracy, enabling rapid structure-based drug design; this approach allowed researchers to identify and optimize a potent CDK20 inhibitor within 30 days, even without experimental structural data - ML applied to nationwide EHR identified existing drug classes potentially protective against Parkinson's disease, demonstrating AI's potential in drug repurposing
	Drug testing	*Target population identification:* - Unsupervised ML techniques enable the stratification of heterogeneous patient populations, such as in systemic sclerosis or Sjogren's syndrome, by uncovering immuno-clinical subgroups with distinct therapeutic responses, improving trial efficiency and outcome specificity compared to traditional broad inclusion criteria *Clinical trial generation:* - AI-generated virtual cohorts and DT simulate patient variability and disease trajectories, allowing the design of adaptive and cost-effective clinical trials, especially in rare or complex diseases where conventional RCTs are impractical or underpowered *Response & adverse effect prediction:* - ML models trained on multi-omics and clinical data predict individual treatment responses, guide real-time dosing (e.g., chemotherapy), and anticipate adverse effects
Pharmacovigilance		AI tools like ML-driven signal detection systems, streamline adverse event reporting, accelerate signal identification from EHRs and literature, and enhance the accuracy and efficiency of safety monitoring beyond what is feasible with manual methods
AI as treatment		Mental health chatbots and emotional health apps improve access to care by providing scalable, evidence-based support for conditions like anxiety and depression, bridging gaps before formal therapy and sometimes serving as standalone or adjunctive therapeutic interventions
Education & follow-up	Patient education	AI enhances patient education and engagement by simplifying complex medical information for better understanding, delivering personalized guidance via chatbots and robots, and significantly improving medication adherence through interactive support tools
	Patient follow-up	AI supports ongoing patient management by automating symptom monitoring and health assessments through tools like chatbots and AI-driven telephone follow-ups, enabling timely clinical interventions. Additionally, AI-powered prediction of no-show risks combined with automated reminders significantly improves appointment adherence and clinic efficiency

DL: deep learning; DT: digital twin; EHR: electronic health record; ML: machine learning; RCT: randomized control trials; TNIK: TRAF2- and NCK-interacting kinase.

tic model — was developed to predict sepsis onset up to 48 hours in advance using routine electronic health record (EHR) data outside the intensive care unit [19]. In a cohort of over 82,000 hospital admissions, SepsisFinder outperformed the widely used NEWS2 score, achieving higher AUC (0.950 vs. 0.872) and better precision-recall performance, while also triggering alerts earlier. Importantly, it provided a median lead time of 5.5 hours before antibiotics were administered, highlighting its potential to improve early detection of sepsis and clinical outcomes.

Overall, these examples illustrate how AI-driven early detection strategies can expand therapeutic options and significantly improve patient prognosis, even though ensuring robustness across diverse populations and clinical settings remains an ongoing challenge.

Precision and differential diagnoses

Thanks to its intrinsic capabilities — including pattern recognition, multidimensional data integration, and probabilistic reasoning — AI has the potential to greatly assist clinicians in establishing more precise diagnoses and identifying or ruling out differential diagnoses.

For example, Dr. Xue et al. developed an AI model that integrates diverse clinical, cognitive, and imaging data to distinguish among 10 distinct causes of dementia across a

Table 2 Definitions of metrics used to evaluate model performance in the discussed examples.

Evaluation Metrics	Definitions [87,88]
Accuracy	The proportion of correct predictions made by a model across all evaluated cases
Concordance index	Index which measures the ability of a predictive model to correctly rank the order of outcomes, commonly used in survival analysis. It reflects the probability that, for a randomly chosen pair of individuals, the model assigns a higher risk to the individual who experiences the event earlier
Error rate	The proportion of incorrect predictions made by a model out of all evaluated cases
F1 score	Score that combines how many correct positive results the model gives (precision) and how many real positive cases it finds (recall) into a single number
Flesch-Kincaid grade level	A readability score that indicates the approximate U.S. school grade level required to understand a given text. Higher scores correspond to more complex texts, while lower scores indicate greater readability
Sensitivity (recall)	The ability of a model to correctly identify true positive cases (the proportion of actual positive cases the model detects)

large, multi-site cohort of over 51,000 individuals [20]. This model achieved high diagnostic accuracy (AUC up to 0.96), maintained strong performance even with incomplete data, and improved neurologists' diagnostic accuracy by over 26% when used as a support tool.

Similar machine learning approaches have been successfully applied to differentiate other neurological conditions, such as distinguishing frontotemporal dementia from Alzheimer's disease [21], or Parkinson's disease from essential tremor [22].

Beyond neurology, AI methods have also shown promise in tackling difficult diagnoses in other fields. For instance, a recent systematic review and meta-analysis evaluated the performance of ML models in distinguishing Kawasaki disease (KD) from other febrile illnesses and predicting coronary artery lesions (CAL) in KD patients [23]. Analyzing data from 29 studies encompassing over 100,000 participants, the review found that ML models achieved a pooled concordance index of 0.898 (95% CI 0.87—0.92), with a sensitivity of 0.91 (95% CI 0.83—0.95) and a specificity of 0.86 (95% CI 0.80—0.90) for differentiating KD from other febrile conditions. Additionally, ML models reached a pooled concordance index of 0.79 (95% CI 0.74—0.84) for predicting CAL in KD patients.

Despite the need for careful validation across diverse patient cohorts to avoid biases and potential misclassification, these findings highlight how ML models, by leveraging commonly available clinical data, can effectively support a more accurate diagnosis and help discard potential differential diagnoses, thereby enhancing clinical decision-making and improving patient outcomes.

Early relapse detection/disease progression prediction

AI can also contribute to predicting disease course, particularly by enabling earlier relapse detection or identifying potential patterns of disease progression. As an example, a recent study assessed the performance of various ML algorithms in predicting relapse and mortality among pediatric acute lymphoblastic leukemia (ALL) patients [24]. Analyzing data from 161 children under 16 years of age, the researchers found that boosting and random forest algorithms achieved the highest predictive performance, with accuracy rates up to 84% and strong AUC scores. Key prognostic factors for relapse prediction included age at diagnosis, white blood cell count, hemoglobin levels, and platelet count. These findings suggest that ML models, can effectively predict relapse in pediatric ALL and potentially support clinicians in tailoring treatment and follow-up strategies.

Similarly, Maeda et al. explored the utility of real-time AI-assisted colonoscopy to predict relapse in patients with ulcerative colitis (UC) in clinical remission [25]. In this prospective cohort study, 145 UC patients underwent AI-assisted colonoscopy incorporating a contact-microscopy function. Based on AI outputs, patients were classified into 'Healing' and 'Active' groups. Over a 12-month follow-up, the relapse rate was significantly higher in the AI-Active group (28.4%) compared to the AI-Healing group (4.9%). Predictive models, such as an eXtreme Gradient Boosting (XGBoost) model and a Simplified Risk Score Prediction Model, have been developed to forecast renal flares in lupus nephritis patients following remission [26], offering new tools for individualized patient monitoring and management.

Regarding disease progression, D'hondt et al. presented a machine learning model to predict the timing of disability worsening in multiple sclerosis patients, using data from over 29,000 individuals included in the MSBase registry [27]. By applying a survival analysis approach with random survival forests, the model estimates when significant progression on the Expanded Disability Status Scale is likely to occur. Notably, the model is explainable, providing clinicians with insights into the key factors that influence each patient's risk and the timing of progression, thus supporting earlier and more personalized interventions.

Prognosis

AI's role in predicting disease outcomes is rapidly expanding, offering healthcare practitioners advanced tools to improve prognosis assessment in areas as diverse as oncology, infectious diseases, and critical care [28]. Rather than relying solely on conventional scoring systems, ML models are beginning to incorporate multilayer clinical and biological data to enhance predictive accuracy. For instance, Kinoshita et al. developed an AI model to improve postoperative prognosis prediction in patients with non-small cell lung cancer [29]. Using data from 1049 patients — including 17 clinicopathological variables and over 50 pre- and postoperative blood test parameters — the researchers applied the XGBoost ML algorithm to predict 5-year disease-free survival, overall survival, and cancer-specific survival. The model achieved impressive performance, with AUCs of 0.890, 0.926, and 0.960, respectively, outperforming traditional staging systems and offering clinicians a more precise tool to assess patient prognosis and guide postoperative treatment strategies.

Similarly, a Korean research team aimed to improve the prediction of 30-day mortality in pneumonia patients by integrating AI-derived chest radiograph (CXR) scores with clinical parameters [30]. Analyzing data from 489 adults hospitalized for pneumonia between March 2020 and August 2021, they developed a prognostic model combining AI-based CXR consolidation scores with CURB-65 scores, initial oxygen requirements, and intubation status. This integrated model achieved a concordance index of 0.726 in the test cohort, outperforming traditional tools such as CURB-65 and the Pneumonia Severity Index. These findings highlight the added value of combining AI-analyzed imaging with established clinical predictors for refining prognosis assessment.

Treatment

Therapeutic target

AI has also emerged as a powerful tool for identifying key biological pathways involved in disease pathophysiology, thereby guiding the discovery of novel therapeutic targets.

An international research team at in silico medicine utilized its AI-driven platform, Pharma.AI, to analyze large-scale omics datasets and identify TNIK (TRAF2 and NCK-interacting kinase) as a novel contributor to fibrosis [31]. Through the integration of transcriptomic, proteomic, and disease association data, TNIK was pinpointed as playing a central role in fibrotic signaling pathways. Based on this discovery, the researchers developed INS018_055, a small-molecule TNIK inhibitor that demonstrated strong anti-fibrotic effects in preclinical models and showed safety and tolerability in a phase I clinical trial for idiopathic pulmonary fibrosis.

Similarly, Schuh et al. introduced an end-to-end pipeline leveraging AI to uncover novel antibiotic mechanisms [32]. A key innovation of their approach lies in the target selection phase, where the system analyzes proteomes from multiple bacterial pathogens to identify essential, conserved proteins that lack human homologs — thus ensuring both efficacy and safety. Notably, many of the targets revealed through this AI-based approach fall outside the traditional scope of antibiotic development, which has historically focused on a narrow subset of bacterial functions. By prioritizing previously untapped bacterial pathways, this strategy opens the door to discovering antibiotics with entirely new mechanisms of action, a critical advancement in the fight against antibiotic resistance.

Drug discovery and design

Building on previous findings, AI can also be employed to facilitate the discovery of new therapeutic molecules or to repurpose existing drugs.

In the design of novel drugs, beyond their capabilities in pathway identification, AI-based tools offer unprecedented opportunities. For instance, AlphaFold, a DL system developed by DeepMind, predicts the 3D structure of proteins from their amino acid sequences with remarkable accuracy [33]. By enabling precise predictions of protein structures —- even in the absence of experimental data — AlphaFold allows researchers to model novel drug targets implicated in disease pathways. These structural insights help identify binding pockets and support the rational design of small-molecule inhibitors through structure-based drug design strategies. Additionally, AlphaFold facilitates virtual screening against predicted protein conformations, significantly accelerating early-stage drug discovery and enhancing the development of innovative therapies. For example, a study by Ren et al. utilized an AlphaFold-predicted structure of CDK20, a kinase associated with hepatocellular carcinoma, where no experimental structure was available. During a one-month period, the authors were able to identify and optimize a potent small-molecule inhibitor. The final compound showed nanomolar binding affinity and demonstrated effective antiproliferative activity in hepatocarcinoma cell lines, underscoring its therapeutic potential [34].

AI can also leverage the massive amounts of real-world data available, offering opportunities for drug repurposing that would be challenging to achieve through traditional methods. For example, French researchers applied ML algorithms to large-scale EHR from the French national database to identify drugs potentially associated with a reduced risk of developing Parkinson's disease [35]. Their analysis highlighted six drug classes—including furosemide, nicotine dependence treatments, and insulin analogues—that may confer protective effects. This could provide a cost-effective and time-efficient strategy to accelerate the development of treatments for complex diseases.

Drug testing

Target population

Accurate selection and targeting of patient subgroups are crucial to optimize drug efficacy. The therapeutic success of a drug often depends not only on its pharmacological properties but also on identifying the population most likely to benefit from it. In this regard, unsupervised ML techniques, such as clustering algorithms, have proven valuable in uncovering distinct clinical and immunological phenotypes within diseases traditionally considered homogeneous, such as systemic sclerosis [36] and Sjogren's syndrome [37]. These subgroups can differ substantially in their underlying disease mechanisms, progression patterns, and therapeutic responses.

AI-driven patient stratification thus enables a more personalized approach to clinical trial design by helping define which subpopulations should be included to maximize the likelihood of demonstrating treatment efficacy. For instance, in trials evaluating Ianalumab for Sjogren's syndrome [38], stratification based on B-cell activation profiles could enrich the study cohort with patients more likely to respond. Such strategies not only improve trial efficiency and the robustness of outcome interpretation but may also accelerate the development of more targeted and effective therapies.

Clinical trial generation

Beyond patient selection, AI is increasingly playing a transformative role in the design and simulation of clinical trials, particularly in settings where traditional randomized controlled trials (RCT) face significant logistical, financial, or ethical constraints. While RCT remain the cornerstone of clinical research, their feasibility can be limited in rare diseases, highly specific subpopulations, or rapidly evolving medical emergencies, where recruiting sufficiently powered cohorts becomes extremely challenging. To address these barriers, AI-driven tools such as virtual cohorts and digital twins (DT) have emerged as innovative and complementary strategies.

Virtual cohorts refer to synthetic populations composed of non-identical but statistically equivalent patient data sets that accurately replicate the variability and clinical features of real-world groups [39]. These virtual populations can be used to simulate clinical trials, expand dataset sizes, improve statistical power, and test hypotheses before initiating costly and time-consuming real-world studies. In particular, virtual cohorts have shown substantial value in neurodegenerative disease research [39], where long disease courses and heterogeneous presentations complicate traditional trial designs. Similar approaches have been explored in cardiovascular medicine [40] and hematology [41], and will be used soon in a wide range of therapeutic areas.

Building upon the concept of virtual cohorts, DT offer an even more personalized and dynamic application of AI in clinical trial design. A DT is a continuously updated mathematical model of an individual patient, capturing their evolving biological, physiological, and clinical characteristics over time [42]. Unlike static models, DT can simulate real-time responses to therapeutic interventions, disease progression, and changes in clinical parameters, allowing for more accurate predictions and informed decision-making. This dynamic modeling capability enables the virtual testing of different treatment strategies, facilitates adaptive trial designs, and helps anticipate potential adverse effects.

In cardiology, for example, DT have been utilized to simulate organ-drug interactions and optimize procedural planning, as demonstrated by Dassault Systèmes' ''Living Heart'' project [43]. In oncology, DT models have shown promise in predicting individual responses to chemotherapy and radiotherapy [44,45], offering a new frontier for personalized medicine. By enabling iterative, patient-specific simulations, DT may one day reduce reliance on large trial cohorts, lower development costs, and accelerate the delivery of effective therapies to the right patients at the right time.

Response and adverse effect prediction

AI is also playing an increasingly pivotal role in personalizing medical treatments by predicting individual responses to therapy, optimizing dosing strategies, and anticipating potential adverse events. ML models trained on genomic, transcriptomic, and clinical data have demonstrated high accuracy in forecasting how specific patients will respond to therapeutic agents [46]. For instance, a 2018 study published in *Scientific Reports* demonstrated that ML algorithms could predict cancer drug responses with remarkable precision by integrating molecular features with drug sensitivity profiles, thereby enabling clinicians to better tailor treatments to the unique biology of each patient's tumor [46]. Similarly, in psychiatry, an AI-assisted model trained on EHR successfully identified patient subgroups most likely to benefit from specific classes of antidepressants, potentially reducing trial-and-error prescribing and accelerating the time to therapeutic benefit [47].

Beyond predicting treatment responses, AI technologies are increasingly being utilized to dynamically determine optimal drug dosing for individuals. One notable example is the CURATE.AI platform, prospectively trialed in patients undergoing chemotherapy. This AI-driven system dynamically adjusted chemotherapy doses in real-time based on each patient's specific biological responses, demonstrating the feasibility of fine-tuning dosing to maximize efficacy while minimizing toxicity [48]. Similar approaches have been applied in other therapeutic domains; for instance, deep neural networks were leveraged to guide warfarin dosing by incorporating clinical and demographic variables, significantly outperforming traditional dosing algorithms [49]. In nephrology, AI-based strategies are being explored to personalize pharmacotherapy in dialysis patients, a group with particularly complex and variable pharmacokinetics [50].

In addition to optimizing efficacy and dosing, AI's predictive capabilities extend to forecasting adverse events. By analyzing large-scale health datasets and integrating omics information, predictive models are being developed to anticipate side effects before they clinically manifest [51]. Such early warnings could allow preemptive dose adjustments, therapy switches, or closer monitoring, ultimately enhancing patient safety and reducing the burden of treatment-related complications on healthcare systems.

Complementing purely predictive approaches, emerging methods in causal learning are being explored to uncover the underlying cause-and-effect relationships that drive treatment outcomes. For instance, a recent study by Verstraete et al. [52] applied causal ML, specifically causal forests, to randomized controlled trial data to estimate how individual chronic obstructive pulmonary disease (COPD) patients respond to inhaled treatments. Unlike traditional prediction methods that focus on overall outcomes, causal learning helped determine the actual treatment effect for each patient by separating the impact of the therapy from other factors. This made it possible to identify which patients gained the most benefit, revealing important differences in treatment response linked to clinical features like lung function and blood eosinophil levels.

Pharmacovigilance

AI is revolutionizing pharmacovigilance by optimizing case documentation, accelerating signal detection, and enhancing adverse event prediction. A prime example is Bayer's MyGenAssist, a ChatGPT-based language model designed specifically for pharmacovigilance teams to draft case documentation letters. A study demonstrated that using MyGenAssist drastically cut down documentation time and reduced administrative burden, enabling pharmacovigilance professionals to focus on more strategic, high-value tasks [53].

Additionally, research by Sorbello et al. and Martin et al. highlighted how ML models are transforming the early detection of safety signals. These models leverage automated data mining across spontaneous reporting systems, EHR, and scientific literature to identify potential adverse drug reactions faster and with greater accuracy than traditional manual methods [54,55]. As AI systems evolve to become more sophisticated and context-aware, their role in automating reporting processes and predicting risk patterns in pharmacovigilance will only grow, making them essential tools in the field.

AI as treatment

The development of AI and its increasing availability to the general public make it a potentially handy tool and could represent a therapeutic weapon in itself. This is especially relevant in the field of mental health. Indeed, in recent years, numerous tools have been designed to help manage conditions like anxiety or depression, ranging from chatbot-based therapies to emotional health apps, with promising outcomes in improving access to care and overall psychological well-being. These AI-driven tools can help improve mental health on a daily basis and bridge the gap between intimidating consultations and the start of therapy, providing support during often lengthy waiting periods and easing the first step for individuals who might otherwise avoid seeking help or would not have access to mental health practitioners. Some of these tools can also be of great value to healthcare professionals, assisting in early diagnosis, monitoring patient progress, and offering evidence-based therapeutic suggestions. As such, AI not only complements traditional care but, in some cases, may represent a first line of support or even a standalone therapeutic intervention [56—58].

Patient education and follow-up

AI is increasingly playing a pivotal role in patient follow-up and education, offering personalized support to individuals throughout their healthcare journey. Various AI models have been developed and integrated into clinical practice to enhance patient understanding of their conditions and provide ongoing guidance, helping them manage daily challenges and potential health concerns.

Patient education

AI can be a valuable tool in improving patients' understanding of their condition, thus contributing to a better observance, therapeutic alliance, and patient as actor of their disease. This can be achieved by improving and making scientific literacy more accessible to the general public. For instance, Patel et al. evaluated the effectiveness of ChatGPT-4 in simplifying otolaryngology-related patient education content [59]. Initially, 71 articles from the American Academy of Otolaryngology-Head and Neck Surgery (AAO-HNS) had an average Flesch-Kincaid Grade Level (FKGL) of 11.03. After AI intervention, the average FKGL decreased to 5.80, aligning with the recommended sixth-grade reading level. Importantly, the AI-modified materials maintained factual accuracy and sufficient detail for patient education. A similar approach assessing different chatbots was employed in the field of nephrology, in a study exploring the integration of AI technologies to enhance patient understanding and engagement in kidney health management [60].

Hospital discharge is often a critical transition point, especially for patients recovering from acute conditions like heart failure. At the IHU ICAN (*Institut hospitalo-universitaire de cardiologie et nutrition*) in Paris, this challenge inspired the development of the ROB'EDUC program, an initiative that embeds AI into therapeutic education [61]. During hospitalization for acute decompensated heart failure, patients interact with a humanoid robot that delivers tailored guidance on recognizing early warning signs, adhering to medication, and following a sodium-restricted diet. What sets the program apart is its continuity: after discharge, a mobile application takes over, reinforcing key messages and supporting long-term self-management. In doing so, ROB'EDUC offers a model of how AI can personalize care across the hospital—home continuum.

Another challenge in healthcare is medication adherence, particularly for long-term therapies like anticoagulation post-stroke. Rather than relying solely on patient motivation or routine follow-ups, AI systems now intervene more dynamically [62]. In one randomized trial, the integration of an AI-driven mobile application into patients' daily routines resulted in full adherence (100%) over 12 weeks, objectively measured through plasma drug concentrations [63]. This figure stood in stark contrast to the 50% adherence rate in the control group, revealing not just improved behavior but measurable biochemical compliance. Interestingly, the most pronounced gains were observed in users of direct oral anticoagulants, where adherence jumped by 67%, highlighting the potential of AI technologies to enhance real-life medication adherence.

Patient follow-up

Besides the aforementioned help in predicting the risk of disease relapse, AI can also help in patient follow-up through different aspects. For instance, certain AI models can help monitor disease activity through patient symptom recording and analysis, identifying the need for medical help. A study assessed the effectiveness of AI-driven telephone follow-ups in managing arterial hypertension [64].

Conducted in Shanghai, 350 hypertensive patients received follow-up calls once by AI and once by a human within a 3—7-day interval. The AI model worked by using automated telephone calls to assess patient health, including symptoms, medication adherence, and lifestyle factors. It followed a structured dialogue where the AI system asked predefined questions based on the patient's medical history. The system then collected and processed responses, evaluating any abnormal data or concerns that warranted further action or follow-up by healthcare professionals. If the AI identified significant issues, it flagged them for the attention of a doctor, ensuring timely interventions. The model was designed to provide a reliable and efficient alternative to human follow-up, with moderate to substantial consistency in responses compared to manual calls.

AI can also help in patient engagement, notably through the use of adequate reminders. The study by AlSerkal et al. evaluated the impact of an AI-driven solution integrated with a real-time dashboard on reducing no-show appointments and improving patient waiting times in primary health care centers [65]. The AI model, with an 86% accuracy rate, predicted no-show risks by analyzing historical data and categorizing appointments accordingly. The AI system then sent automated reminders via SMS or phone calls 24 to 48 hours before the scheduled appointment. These reminders encouraged patients to confirm or reschedule, and healthcare staff could follow-up with high-risk patients, helping to reduce no-shows and improve clinic efficiency. The intervention led to a significant 50.7% reduction in no-show rates and a 5.7-minute decrease in average patient wait times, enhancing operational efficiency and patient satisfaction.

Before a doctor's appointment chatbot-based systems can further engage with patients to gather structured information on symptoms, medical history, or concerns. A recent review published in JMIR Medical Informatics highlighted how chatbots such as ''Edna'' can facilitate efficient history-taking by guiding patients through structured questions prior to their consultation [66]. These tools help ensure that key clinical information is captured accurately and comprehensively, saving valuable time during appointments, and enhancing efficiency.

Preventive medicine

Lastly, AI can play a crucial role in the early prevention of certain diseases, particularly infectious diseases. Over the past decade, ML models have been explicitly developed for predicting and preventing the outbreaks of new pathological agents. For example, BlueDot, a Canadian AI platform, uses NLP and ML to predict infectious disease outbreaks by analyzing diverse data sources such as global news reports, airline ticketing data, and official health communications. This system can detect early signs of emerging health threats and forecast their potential spread. In fact, BlueDot alerted its clients to the COVID-19 outbreak on December 31st, 2019, days before official announcements from the World Health Organization and the U.S. Centers for Disease Control and Prevention [67,68].

In addition to infectious diseases, AI is also making significant strides in primary prevention, particularly in reducing cardiovascular risk. Lifestyle interventions have been shown to greatly reduce the risk of developing cardiovascular diseases or even diabetes — two of the leading causes of death worldwide [69—71]. A recent systematic review by Aggarwal et al. highlighted the potential of AI-driven interventions, especially through interactive chatbots, to promote health behavior changes such as adopting a healthier diet or quitting smoking and substance abuse [72]. These user-friendly and non-judgmental applications are proving valuable in encouraging a healthier lifestyle and reducing the burden of metabolic diseases.

This approach also shows promise in the prevention of complications related to chronic diseases such as type 2 diabetes. In a study by Faruqui et al., participants were divided into two groups over six months: one received daily AI-generated personalized feedback via text messages, while the other received no such intervention [73]. The AI system used a predictive DT, built from each patient's self-monitoring data, such as weight, diet, physical activity, and glucose levels, collected during the first three months. This model, updated weekly, could predict future glucose and weight trends for each individual with over 80% accuracy. Based on these predictions, the system provided personalized recommendations to help patients keep their glucose and weight within healthy ranges, both key to preventing complications. Participants receiving the AI-guided feedback experienced significant weight loss (an average of 5.87 lbs) and better glucose control, highlighting how AI-supported monitoring can help prevent disease complications.

Limitations of AI — practical and ethical considerations

The optimal and ethical deployment of AI in healthcare requires addressing various significant challenges (Fig. 3).

First, algorithmic bias can lead to unequal treatment across populations. AI models are trained on data, and the type of training they receive reflects in their future performance. As a result, if training data lacks diversity (e.g., underrepresents certain ethnicities, genders, or rare diseases), the model may produce biased or less accurate predictions. This was reported in a notable study highlighting racial bias in facial recognition systems [74]. Researchers discovered that leading commercial facial analysis programs struggled to accurately recognize dark-skinned and female faces. Specifically, error rates for darker-skinned women reached up to 34.7%, while the same systems had error rates below 1% for lighter-skinned men. This disparity was primarily attributed to the underrepresentation of diverse faces in the training datasets used to develop these AI models.

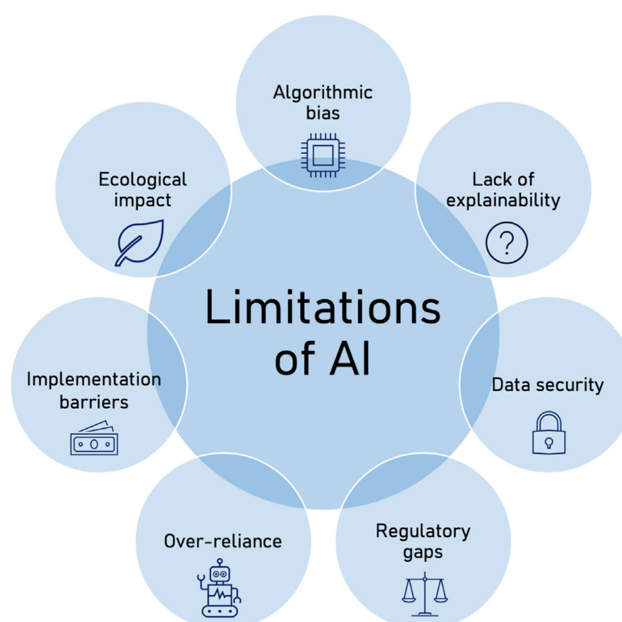

Figure 3. Considerations and limitations in the implementation of artificial intelligence for precision medicine.

Similarly, AI models may perform very well on the data they were trained on but struggle when exposed to different or unexpected data [75], a phenomenon known as overfitting. In these cases, the model ''memorizes'' the training data instead of learning generalizable patterns, limiting its ability to adapt to real-world variability. Overfitting can be mitigated through careful model design, such as using techniques like regularization or validating the model on separate, unseen datasets to ensure it performs reliably beyond its initial training environment. Additionally, datasets should be thoroughly assessed for their diversity and representativeness relative to the intended clinical application. Healthcare professionals should be aware of the importance of providing appropriate input data and recognize the potential risks of relying on AI in atypical or underrepresented cases. Some AI models developed in one healthcare setting or country may not perform well in others due to differences in populations, clinical practices, or health systems, underscoring the need for cautious validation before broader deployment. Finally, another algorithmic bias may come from data leakage. Data leakage occurs when information that would not be available for a model at the time of prediction inadvertently enters the training dataset, artificially inflating performance [76]. This issue can arise from improper dataset splitting or inclusion of post-outcome information and can cause models to fail when applied in real-world clinical settings. Mitigating this risk requires careful separation of training and validation datasets, exclusion of features unavailable at prediction time, and rigorous validation with a domain expert [76].

Second, the lack of transparency in many AI systems (''black boxes'') may undermine clinician trust. Indeed, some of these models are difficult to interpret as the parameters used by the algorithm to make their prediction or decision are often not available to the user [77]. As a result, clinicians may hesitate to trust or act on a recommendation they cannot fully understand or explain to the patient. To address this issue, more recent DL algorithms emphasis on ensuring good explicability in addition to good performance of the model [78]. This detailed information can in turn enable the expert healthcare provider to analyze the relevance of the selected features or outcomes. Promoting the use of explainable AI models can help ensure that decision-making processes are interpretable. It is indeed important for instance to provide access to data visualization tools, particularly for the most discriminative features, to present, through an intelligible interface, the steps followed by the algorithm and the level of confidence in its output. In addition, suggesting alternative options, citing relevant references, and offering contextual information can further support transparency and trust in AI-assisted decisions.

Third, privacy and data security are paramount, as AI systems often require access to sensitive patient information, including genomic data, lifestyle habits, and EHR. Ensuring compliance with applicable regulations like the general data protection regulation [79] is essential to protect patient confidentiality and maintain trust. Moreover, for AI tools to be deployed clinically, they must meet strict regulatory standards such as the medical device regulation and the recent AI Act in Europe [80], which govern the safety, performance, and responsible use of AI-based medical devices. These regulations act as safeguards to ensure that AI systems are reliable, safe, and secure before being used in patient care. To ensure patient data privacy and security when deploying AI in healthcare, several technical safeguards are commonly employed alongside regulatory frameworks [81]. Data anonymization and pseudonymization are fundamental techniques that involve removing or masking personally identifiable information to minimize re-identification risks while allowing data analysis [82]. Federated learning is an emerging approach that enhances privacy by enabling AI models to be trained across decentralized datasets—such as those held by different hospitals—without the need to transfer sensitive patient data [83]. Additionally, differential privacy introduces controlled statistical ''noise'' into datasets, ensuring individual records cannot be traced while maintaining the integrity of aggregate analyses [84]. Encryption, both at rest and in transit, is critical for preventing unauthorized access to health data during storage or transmission [85]. Finally, robust access controls and audit trails are implemented to restrict system access to authorized personnel only and to maintain accountability through logged activity monitoring. These combined strategies form the technical backbone of secure, privacy-conscious AI deployment in modern healthcare systems.

From a regulatory and legal perspective, the rapid advancement of AI technologies has outpaced the development of clear guidelines and accountability frameworks. Determining liability in cases where AI-driven decisions lead to adverse outcomes remains a complex issue. In France, physicians remain legally accountable for medical decisions, even when assisted by AI tools. In the United States, physicians may be held liable if they fail to exercise appropriate judgment when using AI tools. However, if an AI system operates autonomously and causes harm, determining liability becomes more complex, potentially involving developers or manufacturers. The EU is working on the AI liability directive, aiming to harmonize rules across member states. The directive aims to clarify liability issues, particularly regarding high-risk AI systems, by establishing clear responsibilities for developers, providers, and users. Establishing legal frameworks that define the roles and responsibilities of clinicians, developers, and institutions can clarify liability.

Disparities in access to AI tools could risk exacerbating existing health inequalities. A major challenge lies in the clinical integration of AI solutions within established healthcare workflows, which requires interoperability with EHR systems, thorough training of healthcare professionals, and potentially redesigning current procedures to accommodate new technologies. Therefore, ensuring comprehensive AI education for clinicians and prioritizing interoperability during the design of new tools and infrastructure are essential steps. Additionally, the substantial costs and infrastructure demands associated with developing, validating, and maintaining AI systems may be prohibitive for many institutions, especially those in resource-limited settings, further widening gaps in healthcare access and quality.

The ecological impact of AI cannot be forgotten. AI's ecological impact in healthcare stems primarily from the energy-intensive nature of training and deploying large models used for tasks like medical imaging analysis, diagnostics, or personalized treatment recommendations [86]. These processes require significant computational power, contributing to high electricity consumption and substantial carbon emissions. Additionally, AI infrastructure in healthcare (e.g., cloud-based EHR systems or remote patient monitoring) demands continuous data storage and processing, which increases environmental strain through both energy use and e-waste [86]. As healthcare adopts more AI-driven tools, integrating sustainable practices — like optimizing models for efficiency and using renewable-powered data centers — will be essential to balance innovation with ecological responsibility.

Lastly, over-reliance on AI might reduce clinician autonomy and patient involvement; AI should be designed to support, not replace, human judgment, ensuring clinicians remain central to decision-making. Patient trust and acceptance are also crucial for the successful deployment of AI in healthcare. Patients may be apprehensive about algorithm-based decisions, emphasizing the need for transparency, effective communication, and the assurance that AI serves as a tool to support, not replace, human judgment.

Conclusion

AI is increasingly positioned to become a foundational tool in precision medicine, offering new avenues to optimize drug therapy, predict treatment responses, and contribute to more personalized care pathways. While techniques continue to evolve, their integration must be accompanied by thoughtful consideration of ethical, technical, and regulatory challenges. Nevertheless, AI has the potential to be a reliable ally in advancing personalized care and supporting the ongoing evolution of healthcare practices.

Disclosure of interest

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The other authors declare that they have no competing interest.

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