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Review Article

Ai-Driven Precision Oncology: Revolutionizing Personalized Cancer Therapy

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ABSTRACT

Precision oncology is an approach in which cancer treatment is selected according to the molecular, genomic and clinical characteristics of an individual patient and tumour. Artificial intelligence (AI), including machine learning, deep learning and natural language processing, can analyses large and complex datasets generated by genomics, pathology, radiology and electronic health records. AI may help identify actionable biomarkers, predict treatment response and resistance, support drug discovery, match patients to clinical trials and anticipate adverse drug reactions (ADRs). This review describes the principles of AI-driven precision oncology, major biomarkers, pharmacogenomics, mechanisms of selected targeted and immune therapies, drug-specific adverse effects, AI-assisted toxicity prediction, clinical workflow, advantages, limitations, ethical considerations and future directions. Selected therapies including osimertinib, trastuzumab, dabrafenib/trametinib, olaparib and pembrolizumab demonstrate how molecular findings can be translated into individualized treatment. The future of oncology is likely to involve multimodal AI combined with longitudinal molecular monitoring and multidisciplinary clinical decision-making.

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INTRODUCTION

Cancer is a heterogeneous group of diseases in which genetic and epigenetic alterations drive uncontrolled cell growth. Patients with the same anatomical cancer type may have substantially different molecular profiles and may therefore respond differently to the same treatment. Conventional treatment based mainly on tumor site and stage can consequently result in variable outcomes. Precision oncology attempts to address this problem by incorporating molecular information into therapeutic decision-making. [1,2]

AI provides computational methods for analyzing high-dimensional data that may be difficult to integrate using conventional statistical approaches. In oncology, AI can learn patterns from genomic profiles, digital pathology, radiological images, laboratory results, treatment records and clinical outcomes. The objective is not simply to predict disease but to generate clinically useful information for selecting, monitoring and adapting therapy. [3,4]

The development of targeted therapies and immunotherapies has increased the importance of biomarker testing. EGFR, HER2, BRAF, BRCA1/2, ALK, ROS1, RET, NTRK, KRAS, PD-L1 and mismatch-

repair/microsatellite-instability status are examples of molecular characteristics that may influence treatment selection in appropriate clinical settings. [5,6]

AI therefore has the potential to connect three major components: molecular characterization, therapeutic selection and longitudinal monitoring. Its use must, however, be supported by rigorous validation, appropriate clinical oversight and protection of patient data. [3,7]

PRECISION ONCOLOGY CONCEPT

Precision oncology integrates tumor biology with patient-specific clinical information. Molecular testing may identify mutations, gene fusions, copy-number changes, protein expression or DNA-repair abnormalities. The result is interpreted together with cancer type, stage, previous treatment, organ function, performance status and patient preferences. [1,5]

Table 01: Simplified Precision-Oncology Pathway.

PATIENT	TUMOUR SAMPLEM	OLECULAR TESTIN	GAI / DATA ANALYSIS	BIOMARKER PER	SONALISED THERA	PYMONITORING
Clinical data	Biopsy / blood	NGS / IHC / ctDNA	ML + clinical data	Actionable target	Targeted / immune	Response + ADR

ROLE OF ARTIFICIAL INTELLIGENCE

Machine Learning

Supervised learning can predict outcomes using labelled clinical datasets, while unsupervised learning can identify molecular clusters or patient subgroups. Classification and regression models may support response or toxicity prediction. [3,4]

Deep Learning

Deep neural networks can analyse complex imaging and pathology data. Convolutional neural networks have been investigated for tumor detection, segmentation and histopathological classification. [8,9]

Natural Language Processing

NLP can extract diagnoses, medications, laboratory findings, adverse events and biomarker information from clinical notes and medical records. [3,4]

Multi-Omics Integration

AI can integrate genomic, transcriptomic, proteomic and clinical data to identify biological patterns and potential therapeutic targets. [3,4]

Drug Discovery

AI can assist target identification, molecular screening, prediction of drug–target interactions and prioritization of candidate compounds, potentially reducing time spent in early drug discovery. [10]

BIOMARKERS AND MOLECULAR PROFILING

Biomarkers are measurable characteristics that provide information about a biological process, disease state or treatment response. Companion or complementary diagnostic testing can help determine whether a patient is likely to benefit from a particular therapy. [5,6]

Table 02: Biomarker Interpretation.

Biomarker	Common clinical relevance	Therapeutic example
EGFR mutation	Selected NSCLC	Osimertinib
HER2 amplification/over expression	Breast and other cancers	Trastuzumab
BRAF V600	Melanoma and other cancers	Dabrafenib + trametinib
BRCA1/2 / HRD	Selected breast, ovarian, prostate, pancreatic cancers	Olaparib
ALK rearrangement	NSCLC	ALK inhibitors
ROS1 fusion	NSCLC	ROS1 inhibitors
RET alteration	NSCLC / thyroid cancers	RET inhibitors
NTRK fusion	Tumor-agnostic settings	TRK inhibitors
MSI-H / dimmer	Multiple tumor types	Immune-checkpoint inhibitors
PD-L1 expression	Several cancers	Selected PD-1/PD-L1 inhibitors

Biomarker interpretation is context-dependent; not every biomarker is appropriate for every tumor type, and treatment eligibility depends on current evidence, regulatory status and clinical guidelines. [5,6]

AI-DRIVEN CLINICAL WORKFLOW

Table 03: AI-supported Precision Oncology Workflow.

	Patient assessment	**History, stage, performance status, laboratory data**
	Sample acquisition	Tumor biopsy / blood / liquid biopsy
	Molecular & imaging analysis	NGS, IHC, pathology, radiology, ctDNA
	AI-assisted integration	Machine learning + clinical and molecular datasets
	Biomarker identification	Actionable mutation / pathway / immune biomarker
	Therapy selection	Targeted therapy / immunotherapy / trial
	Monitoring	Response, resistance and adverse reactions
	Reassessment	Repeat molecular/clinical evaluation when indicated

MECHANISM OF ACTION OF SELECTED PRECISION THERAPIES

EGFR pathway – Osimertinib

Activating EGFR mutations can promote receptor tyrosine-kinase signaling and downstream pathways such as RAS–RAF–MEK–ERK and PI3K–AKT. Osimertinib is a third-generation EGFR tyrosine-kinase inhibitor designed to inhibit mutant EGFR signaling, including the clinically important T790M resistance mutation. Inhibition reduces proliferative and survival signaling in susceptible tumor cells. [11,12]

HER2 – Trastuzumab

Trastuzumab binds the HER2 receptor and interferes with HER2-mediated signaling. It can also promote antibody-dependent cellular cytotoxicity. HER2-targeted treatment is therefore an example of receptor-directed precision therapy based on tumor biomarker status. [13]

BRAF/MEK – Dabrafenib + Trametinib

BRAF V600 alterations can constitutively activate the MAPK pathway. Dabrafenib inhibits BRAF signaling, while trametinib inhibits MEK, a downstream kinase.

Dual pathway inhibition provides complementary suppression of MAPK signaling. [14]

BRCA/HRD – Olaparib

PARP participates in DNA damage response. In tumors with defective homologous-recombination repair, including selected BRCA1/2-mutated cancers, PARP inhibition can create synthetic lethality and preferentially impair tumor-cell survival. [15]

PD-1 – Pembrolizumab

PD-1 is an inhibitory receptor on immune cells. Pembrolizumab blocks PD-1 signaling and can restore T-cell activity against tumor cells. Response is influenced by tumor and immune biomarkers and the clinical context. [16]

Detailed drug table

Table 04: Mechanism of Action of Selected Precision.

Drug	Target / biomarker	MOA	Major ADRs	Monitoring
Osimertinib	EGFR mutation	Irreversible mutant EGFR-TKI	Rash, diarrhea, paronychia; ILD/pneumonitis, QT prolongation	ECG when indicated; pulmonary symptoms; labs
Trastuzumab	HER2	HER2 blockade + ADCC	Cardiac dysfunction, reactions infusion n	LVEF/ cardiac assessment; infusion monitoring
Dabrafenib + trametinib	BRAF V600	BRAF + MEK inhibition	Fever, rash, ocular/cardiac effects fatigue e;	Temperature e, skin, ocular and cardiac monitoring
Olaparib	BRCA/HRD	PAR P lethal it inhibit on; synthetic ice	Anemia, nausea, fatigue; rare MDS/AML	CBC; renal/ hepatic assessment as appropriate
Pembrolizumab b	PD-1	Immune-checkpoint blockade	Immune-related dermatitis, colitis, hepatitis, pneumonitis, endocrinopathies	Symptoms, LFT, thyroid and other tests as indicated
Alectinib	ALK fusion	ALK tyrosine-kinase inhibition	Myalgia, fatigue, liver changes, bradycardia enzyme e	LFTs, heart rate, symptoms
Larotrectinib	NTRK fusion	TRK inhibition	Dizziness, fatigue, nausea, liver enzyme changes	Liver tests and neurological symptoms

ADVERSE DRUG REACTIONS AND AI-BASED PREDICTION

Adverse drug reactions remain a major challenge even when treatment is molecularly targeted. Precision medicine can reduce exposure to ineffective therapies but does not guarantee absence of toxicity. AI may help identify early signals from laboratory results, medication records, vital signs, imaging and free-text clinical documentation. [3,17]

Table 05: Adverse Drug Reaction and AI- Based Prediction.

Therapy	Important ADRs	Potential AI/clinical signal
EGFR inhibitors	Skin toxicity, diarrhea; rare pneumonitis	Rash documentation, stool symptoms, oxygenation/imaging patterns
HER2 therapy	Cardiac dysfunction	LVEF trends, symptoms, cardiac investigations
PARP inhibitors	Anemia, thrombocytopenia, fatigue	CBC trends, treatment interruptions

Therapy	Important ADRs	Potential AI/clinical signal
Checkpoint inhibitors	Immune-related organ toxicity	LFT/thyroid changes, inflammatory markers, symptom notes
BRAF/MEK inhibitors	Pyrexia, skin, ocular/cardiac toxicity	Temperature, dermatology/ophthalmology findings, ECG/ echo

AI-based ADR prediction should be viewed as an early-warning or decision-support approach. False positives and false negatives can occur, and clinical confirmation is necessary before changing therapy. [3,17]

PHARMACOGENOMICS

Pharmacogenomics evaluates how inherited genetic variation influences drug exposure, efficacy and toxicity. Oncology provides important examples in which genetic information can contribute to safer treatment. DPYD-related variation can increase the risk of severe fluoropyrimidine toxicity. Tumor genomic biomarkers, although distinct from germline pharmacogenomics, also determine whether selected targeted treatments are biologically appropriate. Integrating germline, tumor and clinical information can move precision medicine toward both efficacy and safety. [18,19]

AI can potentially combine pharmacogenomic results with medication history, laboratory values and previous toxicity to generate individualized risk estimates. Such systems require robust validation and careful handling of genetic privacy. [3,18]

APPLICATIONS OF AI IN ONCOLOGY

1. Cancer detection and image-based diagnosis
2. Digital pathology and tumor grading
3. Molecular biomarker discovery
4. Treatment-response prediction
5. Resistance prediction and longitudinal monitoring
6. Clinical-trial matching
7. Drug discovery and repurposing
8. Adverse drug reaction and toxicity prediction Prognostic modelling and survival prediction

ADVANTAGES

AI-driven precision oncology can improve patient stratification by identifying clinically relevant patterns across multiple data types. It may help reduce ineffective treatment exposure, prioritize actionable molecular alterations, support trial matching and detect subtle changes that precede clinically obvious progression or toxicity. From a pharmaceutical perspective, AI can also assist target identification, drug screening and prediction of drug–target interactions. [3,4,10]

However, improved algorithmic accuracy does not automatically translate into improved patient outcomes. Clinical utility must be established through appropriate validation and prospective evaluation. [3,7]

LIMITATIONS AND ETHICAL ISSUES

Data quality and bias

Models can inherit errors and biases present in training data. Under-representation of certain populations may reduce generalizability. [7,20]

Interpretability

Complex models may produce predictions without an easily understandable biological explanation. Explainable AI methods can improve transparency but may not eliminate uncertainty. [7,20]

Privacy

Genomic and clinical datasets are highly sensitive. Secure storage, controlled access and appropriate governance are essential. [20,21]

Clinical validation

Models developed retrospectively may perform less well in new hospitals or populations. External and prospective validation is therefore important. [3,7]

Cost and accessibility

Advanced molecular testing and computational infrastructure may be expensive and may not be equally available to all patients. [20]

Responsibility

AI should support, not replace, clinical judgement. Healthcare professionals must interpret AI outputs in the context of the individual patient. [7,20]

FUTURE PERSPECTIVES

Future systems may integrate single-cell sequencing, spatial transcriptomics, liquid biopsy, digital pathology, radiomics and longitudinal electronic health records. Multimodal AI could create dynamic patient profiles that change as tumor biology evolves. Federated learning and other privacy-preserving methods may support collaboration between institutions while reducing unnecessary transfer of sensitive data. Prospective clinical trials and real-world evidence will be important to determine whether AI-guided precision oncology improves survival, quality of life, safety and cost-effectiveness. [3,4,7]

The pharmacist may have an increasingly important role in interpreting medication-related risks, monitoring ADRs, reviewing pharmacogenomic information, supporting medication optimization and

educating patients about targeted and immune therapies. [18,19]

CONCLUSION

AI-driven precision oncology is transforming the concept of personalized cancer therapy from a largely descriptive approach into a data-integrated clinical strategy. By combining molecular biomarkers with imaging, pathology, clinical information and treatment outcomes, AI can support patient selection, therapeutic matching, resistance assessment and toxicity prediction. Targeted drugs such as EGFR, HER2, BRAF/MEK and PARP inhibitors, together with immune-checkpoint inhibitors, illustrate the importance of matching mechanism with tumor biology. Nevertheless, responsible implementation requires high-quality data, rigorous validation, privacy protection, ethical governance and multidisciplinary oversight. The most appropriate model is therefore human-guided precision oncology in which AI augments the expertise of oncologists, pharmacists, pathologists and other healthcare professionals. [1,3,4]

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