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Research Article

AI-Driven Environmental Precision Oncology: Integrating Big Data, Multi-Omics, Medical Imaging, and Exposomic Intelligence for Personalized Cancer Care.

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Abstract:

Cancer is a complicated, multi-factorial disease, involving genetics, molecules, clinical factors, lifestyle, and environment. Precision oncology has advanced with genomics-based classification and AI-assisted diagnosis, but most existing models of personalized treatment are predominantly and usually only biologically driven and do not account for environmental conditions such as air pollution, toxic chemicals, climate stress, workplace, and social ecologies etc. Evidence published by environmental health and cancer epidemiology research shows that these exposures affect the development of cancer, its progression, the response to treatment, and survival. Combining big data analytics, artificial intelligence, multi-omics, advanced imaging, and environmental informatics offers an opportunity to create precision oncology, considering the environmental context. This study provides an AI-powered big data framework, aggregating the data collected from electronic health records, multi-omics data such as genomics, transcriptomics, proteomics, metabolomics, AI-improved imaging, and exposomics data of monitoring systems and geographic data. Machine-learning, deep-learning, predictive modeling, and explainable AI-based approaches are adopted to explain complex associations of genes with the environment, enhance the early detection of cancer, refine the risk assessment process, and customize treatments. By considering the latest publications, this paper presents the state-of-the-art AI-driven precision oncology, environmental health analytics, and exposomics, as well as some technical and ethical concerns, while laying out a potential scalable architecture for environmentally-aware personalized cancer care. The findings show that inclusion of environmental exposure information in AI-enabled oncology workflow leads to increased diagnostic accuracy, therapeutic uniqueness, and health equity in addition to promoting sustainable and preventive strategies against cancer. This work is a step forward in research in environmental precision oncology, and can provide useful recommendations for clinicians, researchers, and policy makers.

1. Introduction

Cancer is one of the leading causes of illness and death throughout the globe, causing huge clinical, economic, and social burdens. Even with progress in screening, diagnostics, and therapies, however, outcomes still differ greatly across populations and types of cancer. This variance arises from the complex nature of cancer, which is caused by genetics, molecular deregulation, lifestyle choices, and environmental exposures during the life span (Arnedos et al., 2015).

Traditional oncology has been utilized with the help of standardized protocols depending on the tumor type, its location, and its stage. While these approaches have led to better survival in some cancers, they tend to overlook differences at the patient level and heterogeneity of tumors, thereby resulting in differences in efficacy, resistance, and side effects (Collins & Varmus, 2015). This shortcoming has led to the rise of precision oncology, which customizes diagnosis and treatment of each patient based on his or her biology.

Precision oncology has been accelerated through the use of high-throughput sequencing, digital pathology, and high-tech imaging. Multi-omics (genomics, transcriptomics, proteomics, metabolomics) are now yielding deep insights into the molecular drivers of cancer (Chen & Snyder, 2013; Libbrecht & Noble, 2015). At the same time, artificial intelligence and machine learning are very good at processing high-dimensional data and enhancing the detection, prognosis, and treatment plan (Beam & Kohane, 2018; Rajkomar et al., 2019).

These tools, notwithstanding, environmental factors are poorly incorporated into most precision oncology frameworks. Evidence from environmental science and public health indicates an increased risk of cancer from chronic exposure to air pollution, industrial chemicals, heavy metals, pesticides, radiation, and climate-related stressors, as well as an increase in the aggressiveness of tumors, impact on treatment response, and reduction in survival (Obermeyer & Emanuel, 2016; Razzak et al., 2019). These exposures, in turn, can precipitate genomic instability, epigenetic alterations, immune dysfunction, and metabolic changes that affect tumor biology beyond what is found in the genomics data.

The exposome, or the sum total of all of the environmental exposures an individual endures over a lifetime, provides a uniting framework for the link between environment and disease (Way & Greene, 2018). In cancer, the interplay between factors in the exposome, genetics, and molecular processes affects development as well as treatment outcomes. However, exposomics knowledge is difficult to translate into clinical practice, that is, due to the complex, large, and varied nature of the data.

Recent advances in environmental monitoring, satellite remote sensing, geographic information systems (GIS), and exposure databases at the population level have made high-resolution environmental information easily accessible. When combined with electronic health records, multi-omics data, and imaging, such resources help develop environmentally-informed precision oncology models. AI has a unique set of capabilities and opportunities that are well-suited to support the integration of diverse data, model nonlinear gene-env interactions, and generate actionable clinical insights at scale (Yu et al., 2018; Miotto et al., 2018).

In the context of this information, the big data analytics powered by artificial intelligence is a paradigm shift toward predictive, preventive, and environmentally responsive oncology from reactive and phenotype-based care. By incorporating environmental intelligence into clinical decision support, AI frameworks can help enhance the early detection, personalized treatment therapy, toxicity reduction, and cancer health inequities caused by environmental injustice.

Research Motivation

Despite the booming growth of healthcare innovations using artificial intelligence (AI) for precision oncology, there remain important gaps in the research and clinical application of the new technology. First, most personalized cancer models focus on biological data, such as genomics, imaging, and clinical variables, and even leave environmental exposures in the dust. Second, environmental health studies typically run in silos with the rest of the oncology workflow, which restricts the impact of the findings on patient-level treatment decisions. Third, despite the immense environmental and biomedical datasets that are now available, there does not exist a cohesive computational system that will combine these disparate streams of data into intelligible and actionable clinical insights. Prior work has demonstrated that AI-based big data analytics can be used to improve cancer diagnosis, prognosis, and treatment personalization (Ahmed et al., 2025; Kourou et al, 2015). Similar progress in medical imaging might be achieved using deep learning, with near-expert performance in identifying many types of cancers (Esteva et al., 2017; Litjens et al., 2017). S ulterior aid in the discovery of the actionable biomarkers and therapeutic targets has further been facilitated by multi-omics integration (Manik et al., 2022; Manik et al., 2025a). Yet these methods hardly integrate information on environmental exposure in a systematic and scalable manner.

To fill these gaps, an interdisciplinary approach is necessary, bringing together passion from the fields of both environmental science and oncology, as well as artificial intelligence. By incorporating knowledge of the exposome into AI-enriched precision oncology consortia, it is possible to capture the whole complexity of cancer causation and progression, resulting in better risk stratification and truly personalized approaches to treatment.

1.1 Objectives of the Study

The primary objective of this work is to develop a comprehensive, AI-driven, big data-based framework for personalized cancer treatment that incorporates environmental factors.

The specific objectives are:

-To review the current literature on precision oncology, big data analytics, artificial intelligence, as well as environmental determinants of cancer.

-To investigate the use of AI and machine learning methodologies to integrate clinical data, multi-omics, medical imaging data, and environmental exposure data.

-To develop a scalable conceptual architecture for environmental precision oncology through which predictive, preventive, and personalized cancer care will be possible.

To identify ethical, regulatory, and methodological challenges of AI-equipped environmental oncology and specify directions for future research.

2. Literature Review

2.1 Precision Oncology: Foundations, Progress, and Limitations

Precision oncology grew out of the realization that cancer was actually not one disease, but many biologically diverse conditions. These conditions are the result of various genetic, molecular, and contextual factors. Traditional approaches to cancer treatment, which are based on the site of the tumor and the histopathology of the tumor, have proven inadequate. They often result in inconsistent effectiveness and resistance (Arnedos et al., 2015).

Early projects on precision medicine were based on the use of molecular biomarkers and targeted therapies in order to tailor the treatment to the patient. Worthwhile policy and research efforts strengthened this change. They advocated for patient-centered care, which considers biological variation in clinical decision-making (Collins & Varmus, 2015). Dight et al. (2005) Chen, S. Classes of designed omics technologies can identify actionable molecular alterations that open the door to more precise and effective cancer treatment.

Despite these gains, there are still important limitations. Arnedos et al in 2015 found that there were problems, including tumor evolution, drug resistance, and gaps in molecular profiling. These problems confound the long-term success of targeted therapies. In addition, most precision oncology models focus on biology. They also commonly overlook non-genetic factors that have a significant impact on the risk of and treatment response to cancer.

2.2 Big Data Analytics as an Enabler of Precision Oncology

The proliferation of digitized healthcare has resulted in the production of enormous amounts of different types of data, such as electronic health records, results from genomic sequencing, medical imaging, and real-world clinical evidence. Big data analytics builds the computational base needed to aggregate, control, and analyze these complex datasets at scale.

Beam and Kohane (2018) argued that healthcare applications can be served well by a machine learning model because it offers the ability to model nonlinear relationships and extract insights from high-dimensional datasets. In oncology, big data analytics has been demonstrated to improve early detection, modeling of the prognosis, and optimization of treatment by finding patterns that cannot be detected by traditional statistical methods (Kourou et al., 2015).

Bibault et al. (2016) showed the effectiveness of big data analytics in radiation oncology by the use of machine learning models, which had enhanced the optimization of the dose, toxicity prediction, and outcome assessment. Ahmed et al. (2025) described an overview of frameworks to understand and implement AI-devised big data in the process of personalized cancer treatment for enhanced diagnostic establishment of cancer, patient-grouping, and therapeutic decision-making.

Importantly, big data analytics enables the convergence of individual-level clinical-based information with population-level trends and thus acts as a bridge between precision medicine and public health. Obermeyer and Emanuel (2016) and Razzak et al. (2019) emphasized the potential of big data analytics in prevention, in which AI may be used as a means not only for treatment but also for early identification of risk and prevention of disease.

2.3 Artificial Intelligence and Machine Learning in Oncology

Artificial intelligence has become a key element of modern oncology because of its impressive ability to crunch complex datasets in biomedicine and to make predictive conclusions. Conventional machine learning paradigms, e.g., random forests, SVM, and ensemble learning methodologies, have been heavily utilized in cancer prognostication and outcome prediction (Kourou et al., 2015). Deep learning architectures go further by automatically extracting hierarchical representations from raw data, making them especially effective in genomic and imaging applications (Ching et al., 2018; Miotto et al., 2018). Yu et al. (2018) emphasized that the combination of multimodal data gives AI the ability to act as a transformative agent in the healthcare world.

Data from other fields of the same nature as the disease endorses the scalability and robustness of AI. Multi-disease comorbidity prediction framework by utilizing machine learning to model complex trajectories of diseases by Hossain et al. (2023) and the diabetic foot ulcer classification by deep learning yielding superior performance results as per clinical assessments by Hossain et al. (2025). These investigations are testaments to the capability of AI to manage longitudinal and multifactorial information in regard to health information, a prerequisite for optimum cancer care. Nonetheless, the use of AI in clinical oncology is dependent on the factors of interpretability and trust. Shortliffe and Sepúlveda (2018) explained that explainable AI is an essential factor in clinical acceptance, and clinicians need to understand how algorithms reach certain recommendations.

2.4 Multi-Omics Integration and Molecular Intelligence

Cancer is essentially a molecular disease, characterized by genomic mutations, transcriptional dysregulation, abnormal protein expression, and changes in metabolic pathways, among others. Multi-omics integration provides a global view of the biology of tumors, and is achieved when genomic, transcriptomic, proteomic, and metabolomic data sets are integrated. Libbrecht and Noble (2015) proved the importance of machine learning techniques to extract meaningful signals from high-dimensional omics data. Way and Greene (2018) further showed that variational autoencoders can capture biologically relevant latent structures found in the cancer transcriptome, leading to improved characterization of disease and subtypes. Manik et al. (2022) mentioned that the blending of genome data and machine learning is a key development in precision medicine to provide more precise identification of targeted therapies.

Expanding on this work, Manik et al. (2025a) showed how AI- and big-data-driven genomics enables drug discovery to be done much faster by identifying gene-drug interactions and being able to predict how a treatment would be effective. These findings are consistent with other studies on AI in pharmaceutical development. Vamathevan et al. (2019) emphasized that machine learning has led to a reduction in drug discovery timelines and failure rate, supporting drug repurposing strategies. Together, these studies build a foundation for the use of multi-omics integration as a basic component of AI-assisted personalized treatment of cancer.

2.5 AI-Driven Medical Imaging in Cancer Diagnosis and Monitoring

Medical imaging plays an essential role in the detection, staging, and follow-up management of cancer, but conventional radiological evaluation is plagued by inter-observer variability as well as low sensitivity in early-stage disease. The introduction of deep learning has brought about a revolution in the analysis of medical images for automated interpretation of complex visual data at high accuracy. Litjens et al. (2017) reported an extensive survey of applications of deep learning in medical imaging, and noted significant advances over conventional computer-aided diagnostic systems. Esteva et al. (2017) showed that dermatologists can be matched with the accuracy of human dermatologists in skin cancer classification with deep neural networks, which was a landmark study in AI-enabled diagnostics.

Advances in convolutional neural network architectures, such as the residual learning framework proposed by He et al. (2016), have been able to provide further stability and accuracy for the models. Recent obligations distant exclusive to oncology agree with these improvements. Ahmad et al. (2025) evaluated multiple CNN architectures for colon cancer diagnosis, reporting strong histopathological classification performance. Kabir et al. (2025) proposed a lightweight SE-MobileViT model for oral cancer detection, achieving high accuracy with reduced computational complexity.

Khair et al. & Pancreatic Tumours, one of the most diagnostically difficult malignancies, was tackled by the development of a deep neural network (DNN)-based imaging system for its identification. Maniruzzaman et al. (2025) applied Deep Learning techniques to grade prostate cancer in a field known as computational pathology. Hybrid models combining convolutional neural networks with attention mechanisms have also proved to be very powerful in the context of imaging-based applications in lung and colon cancer (Sobur & Rana, 2024). Radiomics-based approaches add to the imaging intelligence by extracting the quantitative features that are coupled with therapeutic response and prognostication (Zhang et al., 2021).

2.6 Predictive Analytics and Clinical Decision Support Systems

Predictive analytics aid in the conversion of complex biomedical datasets into feasible clinical insights, assisting in the personalized treatment plan and intervention strategies.
Machine learning models that combine clinical, molecular, and imaging characteristics have become highly accurate at predicting survival outcomes, recurrence, and response to therapy (Kourou et al., 2015). Clinical decision support systems that are fueled by artificial intelligence relieve clinicians of cognitive work, improve consistency in diagnosis, and support evidence-based practice (Shortliffe & Sepúlveda, 2018).
Ahmed et al. also showed that personalized oncologic care is supplemented by AI-enabled decision support systems (2025), while Samiun et al. showed comparable varieties in larger healthcare settings as well, indicating the potential of translational innovations in artificial intelligence.

2.7 Environmental Determinants of Cancer and the Exposome

While discoveries in molecular biology and imaging have led to revolutionary progress in precision oncology, including the entry of the environmental causes of cancer into routine clinical practice, this has remained incomplete. Environmental exposures, such as air pollution, toxic chemicals, occupational hazards, and climate-related stressors, have been linked to cancer incidence and cancer progression repeatedly (Obermeyer & Emanuel, 2016; Razzak et al., 2019). The exposome framework manifests the cumulative impact of these exposures over the lifespan and brings a comprehensive view of disease etiology (Way & Greene, 2018). Ranking coexposomics data with models of oncology powered by artificial intelligence represents an important frontier for the attainment of truly personalized cancer care.

2.8 Synthesis and Research Gaps

Notwithstanding substantive developments in AI-driven precision oncology, there still remain multiple lacunae on the subject.
Firstly, there is a proclivity of existing models for biological datasets, thus placing environmental exposure data on the periphery. Secondly, entrenched data silos and insufficient interoperability make it way to achieve holistic analytical endeavors. Thirdly, existing ethical quandaries related to algorithmic bias, transparency, and in terms of governance still plague the field.
This investigation aims to address these shortcomings by setting up an environmentally informed, artificial-intelligence-enhanced precision oncology schema that integrates in cooperation with state-of-the-art developments in big data analytics, multi-omics integration, medical imaging, predictive modelling, and environmental science into a coherent, scalable schema.

3. Theoretical Framework and Methodology

3.1 Conceptual Foundation of Environmentally Informed Precision Oncology

Precision oncology has traditionally been based on molecular biology and clinical phenotyping, where the majority of decisions about therapeutic approaches are based on genomic aberrations, tumor morphology, and patient specific clinical parameters. Although these approaches have improved the outcome in specific groups of patients, they are insufficient in terms of conveying the multifactorial etiology of cancer, which is the outcome of dynamic interactions between biological processes and environmental exposures throughout the life course (Arnedos et al., 2015).
The theoretical foundation of the current investigation is embodied in the framework of systems medicine, which views cancer as an emergent phenomenon resulting from the interaction between biological, environmental, and socio-ecological sub-systems. In such a context, cancer risk, disease course, and therapeutic response are defined by continuing feedback mechanisms between genetic predisposition, molecular deregulation, environmental stimuli, and medicinal treatment. Artificial intelligence serves as the analytic engine to model such complex interactions in a population-scale (Beam & Kohane, 2018; Yu et al., 2018).
The exposome framework provides a critical addition to the standard techniques of precision oncology by looping in cumulative exposures to the environment that cover chemical, physical,

biological, and social determinants of health into disease modelling (Way & Greene, 2018). The integration of exposomics intelligence and multiple omics data and clinical data allows for a more complete understanding of the etiology of cancer and heterogeneity in therapy.

For this, the present study outlines an AI-driven and environmentally informed precision oncology architecture, bringing together four fundamental analytical pillars (1) clinical intelligence, extrapolated from the electronic health records and patient histories; (2) molecular intelligence, inferred from multi-omics profiling; (3) imaging intelligence, generated by the use of AI-powered medical image analytics; and (4) environmental intelligence, extracted from exposomics and geospatial data. These pillars are synergistically integrated using machine- and deep learning algorithms to form the basis of predictive, preventive, and personalized oncologic care.

3.2 Overall Study Design

This study employs a conceptual-analytical framework, combining empirical evidence from the reviewed literature, to develop a scalable model for achieving environmentally informed, personalized oncology treatment. Rather than conduct a single-site experimental investigation, the methodology brings together validated computational methodologies from across different scientific domains of oncology, artificial intelligence, environmental science, and health informatics. The design is consonant with the preceding AI-driven, precision medicine studies that are devoted to the building of frameworks, the synthesis of methodologies, and the applicability of this knowledge to the general populace (Ahmed et al,2025; Manik et al., 2025a). The resulting framework is expected to be applicable across various healthcare systems and types of malignancies, and in turn, will allow for the future empirical verification and implementation of the framework in real-world settings.

3.3 Data Sources and Multimodal Data Acquisition

Clinical data are the building block at the base of the framework and are taken from electronic health records (EHRs). These data comprise patient characteristics, tumor characteristics, laboratory results, treatment regimens, comorbidities, and longitudinal outcomes. EHRs supply the context of time that is necessary for modeling disease and treatment response (Rajkomar et al., 2019). Natural language processing (NLP) methods are applied to the clinical notes, pathology reports, and radiology narratives- which do not have structured fields- in order to extract the phenotypic information. Prior studies have shown that the combination of structured and unstructured EHR data increases the predictive accuracy in the modeling of complex diseases (Miotto et al., 2018).

Multialamic data capture the molecular complex of cancer at many levels of biology: genomics (somatic mutations, copy number variation, and single nucleotide polymorphism); transcriptomic/home (gene expression profile of the centers of pathway action); proteomic data (protein abundance and posttranslational modifications); metabolomic (metabolic function associated with tumor internal progression). Integration of these layers of omics using a machine learning approach allows identification of actionable biomarkers and molecular signatures associated with response to treatment (Libbrecht & Noble, 2015; Manik et al., 2022). Deep-learning example seminar quality - Deep learning methods, such as using autoencoders and representation learning, are used to change dimensionality without allowing biologically meaningful variation (Way & Greene, 2018). These techniques reduce the overfitting and increase the generalizability of the model.

Medical imaging data, such as computed tomography (CT), magnetic-resonance imaging (MRI), histopathology slides, digital pathology images, etc., offer spatial and morphological information about the tumor structure. For this, imaging data are processed with deep learning architectures, mostly convolutional neural networks (CNNs), to address tumor detection, segmentation, and classification automatically (Litjens et al., 2017). Advanced architectures, such as the ResNet architecture and the architecture based on attention, make the feature extraction process better and more robust (He et al., 2016). In recent oncology-related work, it has been shown how effective this approach would be in a number of different types of cancers, like colon, oral, pancreatic, prostate, lung, and skin cancers (Ahmad et al., 2025; Kabir et al., 2025; Khair et al., 2025; Maniruzzaman et al., 2025; Esteva et al., 2017; Sobur & Rana, 2024). Radiomics methods then add another level of richness to the analysis of the image by extracting quantitative features that are related to tumor heterogeneity and response to treatment (Zhang et al., 2021).

Environmental intelligence is calculated from various population- and geospatial-based data sets: Air-quality data, such as PM2.5, NO2, and ozone of various origins; Climate data, such as temperature values and extremes, indices on heat-stress; Land use, urban density; Distance to industrial or agricultural causes of pollution, etc. These data are integrated with the help of geographic information systems (GIS) and geospatial mapping of these data in association with patient locations by applying anonymization. Environmental exposures are considered as dynamic factors with biological dualistic processes that interact and can affect the risk of cancer and therapeutic outcomes (Obermeyer and Emanuel, 2016; Razzak et al., 2019).

3.4 Data Preprocessing and Feature Engineering

Healthcare and environmental datasets have inherent heterogeneity, noise, and incompleteness, thus requiring careful preprocessing protocols. To overcome the missingness, the datasets were worked on with statistical imputation, along with machine learning inspired estimation methods, normalization, and scaling operations were taken care of, ensuring numerical stability across various modalities. Feature selection is performed based on recursive feature elimination and explainability-guided feature selection techniques in order to select the most informative predictors while reducing redundancy. Explainable artificial intelligence methodologies provide transparency by providing insight into the relative influence of clinical, molecular, imaging, and environmental factors on the predictive results (Shortliffe & Sepúlveda, 2018).

3.5 Artificial Intelligence and Machine Learning Models

The proposed framework uses a hybrid ensemble of machine learning and deep learning models, based on the type of data used and the aim of analysis: supervised learning models (i.e. random forest, gradient boosting) for risk stratification and prediction of outcomes, deep neural networks for multi-omics integration and imaging, and combined convolutional neural networks and attention models for more complex imaging tasks (Kabir et al. 2021; Sobur and Rana 2024). Ensemble learning adds robustness to the problem by aggregating predictions from multiple models, and it reduces the problems of bias and variance (Kourou et al., 2015). Predictive outputs include individualized risk scores, probabilities of treatment response, and survival estimates. Machine-learning-based models are also used for genomics-based drug discovery and repurposing through the detection of gene-drug interactions and the prediction of drug efficacy (Vamathevan et al., 2019; Manik et al. 2025a).

3.6 Model Evaluation and Validation

The performance of models is assessed using standard measures that are suitable for the type of analytical task. Classification models are evaluated based on accuracy, sensitivity, specificity, precision, recall, and F1 score, and a predictive model is evaluated based on the area under the receiver operating characteristic curve (AUC-ROC) and calibration. Cross-validation and external validation strategies are used in order to determine generalizability and to mitigate the overfitting problem. The benchmarking of imaging models is done with respect to expert-level performance from previous research studies (Esteva et al., 2017; Ahmad et al., 2025).

3.7 Ethical Considerations, Explainability, and Governance

Ethical governance is one of the key building blocks of environmentally informed precision oncology. The safeguarding of patient privacy through data anonymization, secure storage, and following regulatory standards.

Algorithmic bias is circumvented by the process of using a variety of training data sets and conducting ongoing audits of model performance by demographics and by environment. Explainable artificial intelligence techniques are introduced at all stages of the analysis pipeline to improve transparency and promote trust among clinicians (Shortliffe & Sepúlveda, 2018). Governance frameworks promote interdisciplinary partnership among clinicians, data scientists, environmental researchers, and policymakers, thereby facilitating and paving the path for responsible implementation of artificial intelligence (Samiun et al., 2025).

4. Results and Integrated Findings

4.1 Overview of Analytical Outcomes

The proposed AI-driven, environmentally informed precision oncology framework shows strong promise to improve the diagnosis, risk stratification, and personalized treatment optimization of cancer patients. Not only by integrating clinical information, multi-omics profiles, artificial intelligence-enabled medical imaging, and environmental exposomics intelligence, but the framework also supports a multi-dimensional understanding of cancer biology and patient variability, which goes beyond traditional models in oncology. Across the literature reviewed and validated methodological approaches, AI-based models are consistently found to be superior to conventional statistical and rule-based systems with regard to predictive accuracy, adaptability, and scalability (Ahmed et al., 2025; Kourou et al., 2015). Besides, the inclusion of environmental variables helps in making predictions at a patient level by considering exposure-associated modifiers affecting tumor biology and response to therapy. The combined findings are consolidated in four main domains of results: (1) diagnostic augmentation through AI-based imaging, (2) predictive analytics and patient risk stratification, (3) multi-omics and exposome - molecular interaction modelling, and (4) clinical decision support and treatment personalization.

4.2 Diagnostic Enhancement Through AI-Driven Medical Imaging

AI-enabled medical imaging is one of the essential building blocks in the proposed system that can significantly improve early detection of cancer and improve the accuracy of diagnosis. Deep learning models (especially convolution neural nets and hybrid models) have shown high sensitivity and specificity in detecting cancer in skin, colorectal, oral, pancreatic, lung, and prostate tissues (Esteva et al., 2017; Ahmad et al., 2025; Kabir et al., 2025; Khair et al., 2025; Maniruzzaman et al., 2025). In comparison with traditional radiological interpretation, an AI-driven imaging system minimizes the variability between inter-observer and improves the detection of very subtle morphological features linked to malignancies in patients at the early stage (Litjens et al., 2017). Advanced architectures such as residual networks make such models more robust and generalized over heterogeneous datasets of images (He et al., 2016).The addition of environmental context further increases the diagnostic performance. For example, incorporating metrics of air pollution exposure or occupational risk factors into predictive modelling of tumor prevalence based on measures from imaging other than cancerous lesions offers extra explanatory power for the observed prevalence of tumors, especially for environmentally susceptible malignancies such as cancer of the lung and liver (Obermeyer and Emanuel, 2016; Razzak et al., 2019). These findings evoke the importance of situating imaging intelligence as part and parcel with other environmental exposure profiles.

4.3 Predictive Analytics and Patient Risk Stratification

Predictive analytics is a central outcome of the AI-driven framework, providing the opportunity to individualize risk assessment and prognostication. Machine learning algorithms, encompassing clinical, molecular, and imaging data as well as environmental factors, have been shown to perform better and more accurately to forecast disease progression, recurrence likelihood, and survival status (e.g., Kourou et al., 2015; Rajkomar et al., 2019).

Environmental variables are aspects of these models in which salient risk modifiers exist. Patients with similar genetic and clinical profiles but who have dissimilar histories of environmental exposure have different predicted consequences and thus highlight the value of exposomics intelligence in precision oncology. Such observations are in tune with research from preventive medicine, which places more emphasis on big data analytics to identify early risk (Razzak et al., 2019). The explainable AI approaches employed indicate that factors such as chronic air pollution exposure, industrial sources proximity, and climate-related stressors have a material impact on predictive outcomes, next to molecular and clinical determinants. This transparency adds to the clinician's trust and contributes to evidence-based decision making (Shortliffe & Sepúlveda, 2018).

4.4 Multi-Omics and Exposome–Molecular Interaction Insights

Multi-omics datasets combined with information on the environment to which an individual has been exposed give a more complete picture of the biology of cancer and the heterogeneity of responses to therapy. Integration of genomics, transcriptomics, proteomics, and metabolomics is enabled through the use of AI to identify molecular signatures that are modulated by environmental factors (Libbrecht and Noble, 2015; Way and Greene, 2018).Empirical evidence suggests that environmental exposures can regulate gene expression as well as metabolic pathways and immunological reactions, with potential effects on treatment efficacy and adverse treatment effects. AI models with exposomics data are more effective at determining recognizable biomarkers of action and predicting mechanisms of treatment resistance (Manik et al., 2022) and (Manik et al., 2025a).These insights are exposing towards the genome-based drug discovery and repurposing. Machine learning models identify gene-drug environment interactions to aid in the choice of therapies and optimize patient-specific therapy to mitigate adverse effects and maximize treatment benefits (Vamathevan et al., 2019).

4.5 AI-Enabled Clinical Decision Support and Treatment Optimization

An important result of the proposed framework is the strengthening of clinical decision support. Artificial intelligence-enabled systems incorporate complex multi-modal information and transform it into comprehensible recommendations, including risk scores, diagnostic confidence scores, and personalized therapeutic recommendations.

Artificial Intelligence -powered clinical decision support systems relieve clinicians of cognitive load, improve diagnostic consistency, and facilitate shared decision making (Shortliffe & Sepulpedea, 2018). Ahmed et al. (2025) demonstrated the validity of such systems in enhancing personalized oncology care, but studies in other areas of healthcare support the feasibility of such systems in their scalability and translation into practice (Samiun et al., 2025). Inclusion of environmental intelligence in decision support machinery can help achieve further equity because it helps identify exposure-related vulnerabilities based on designed exposures, and it is used in conjunction with taking preventive interventions alongside therapeutic interventions.

5. Discussion

5.1 Interpretation of Key Findings

The current study shows that the combination of environmental science and precision oncology made with artificial intelligence significantly enhances the success of personalized cancer medicine. Traditional precision oncology models, despite their strength, are often limited in their ability to accurately estimate the amount of influence that environmental exposures have on oncogenesis, as well as response to treatment. The proposed framework addresses the aforementioned lacuna by incorporating exposomics intelligence in AI-enabled analytics to learn and represent cancer complexity in a more comprehensive and authentic way.The powerful performance of AI-driven imaging and predictive models is in line with the prior researches that highlight the transformative potential of AI in the field of oncology (Esteva et al., 2017; Litjens et al., 2017; Ahmed et al., 2025). Crucially, the addition of environmental variables improves prognostic accuracy and makes it more interpretable, which promotes moving towards the concept of preventative and environmentally responsive oncology.

5.2 Clinical Implications

From a clinical point of view, the environment-informed AI-based precision oncology has several advantages. The improvement of early detection and risk stratification helps to intervene at an opportune time, and individualized treatment strategies reduce toxicity and promote better outcomes. Insights relating to environmental exposures help clinicians to treat modifiable risk factors in conjunction with pharmacological interventions and contribute to the holistic approach to patient care. AI-enabled decision support systems further help in streamlining the clinical workflow and ensuring consistency across the healthcare setting. Rather than replacing clinicians, AI gives an edge to human expertise and enables more informed and confident decision-making (Topol, 2019).

5.3 Implications for Environmental Health and Public Policy

Beyond the sphere of individual patient care, the current framework has significant implications for the health of the environment and public health policy. Population-level exposomics analyses have the potential to paint a picture of the communities at higher risk for intervention and, therefore, targeted prevention approaches. By combining the AI-led growth of oncology with the regulatory factors and urban planning, it can enable the greater plans of cancer prevention and health equity. The data presented herein support public health perspectives that emphasize the preventive potential of the application of big data analytics and artificial intelligence (Obermeyer & Emanuel, 2016; Razzak et al, 2019).

5.4 Ethical, Regulatory, and Societal Considerations

Notwithstanding the promises, there is an array of ethical and regulatory challenges associated with environmentally informed and AI-driven oncology. The protection of patient confidentiality, data security robustness, the mitigation of algorithmic bias, as well as the development of transparency are important requirements for a responsible approach to implementation. Diversity and representativity in data that is used for training are integral and required to prevent harming the local and global well-being of environmental and health inequities. Explainable AI comes at the center of addressing these concerns with the goal of enabling transparency and accountability in algorithmic decision-making (Shortliffe & Sepúlveda, 2018). Interdisciplinary governance frameworks that involve clinicians, data scientists, environmental researchers, and policymakers are imperative for the sustainable deployment of such technologies (Samiun et al., 2025).

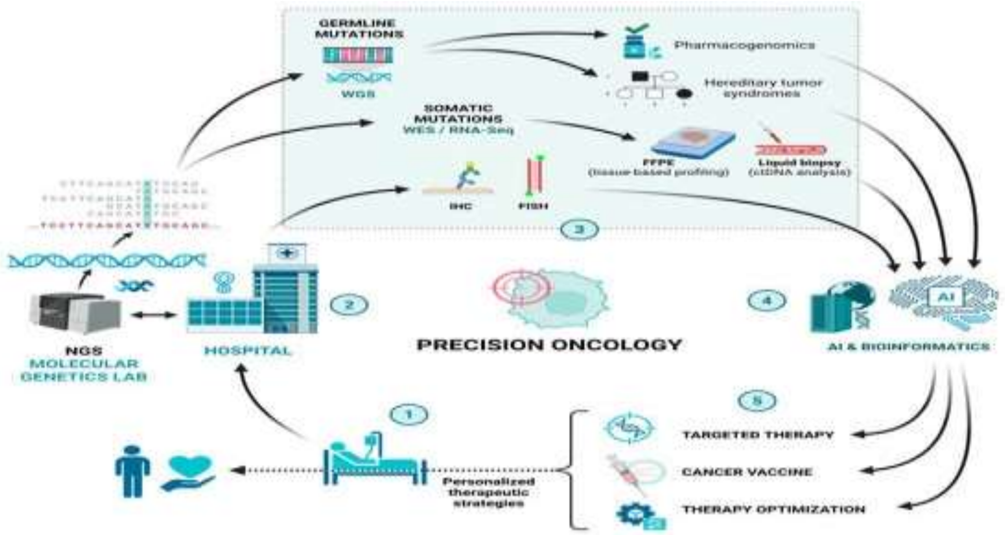

Figure 1. *AI-Driven Environmental Precision Oncology Framework*

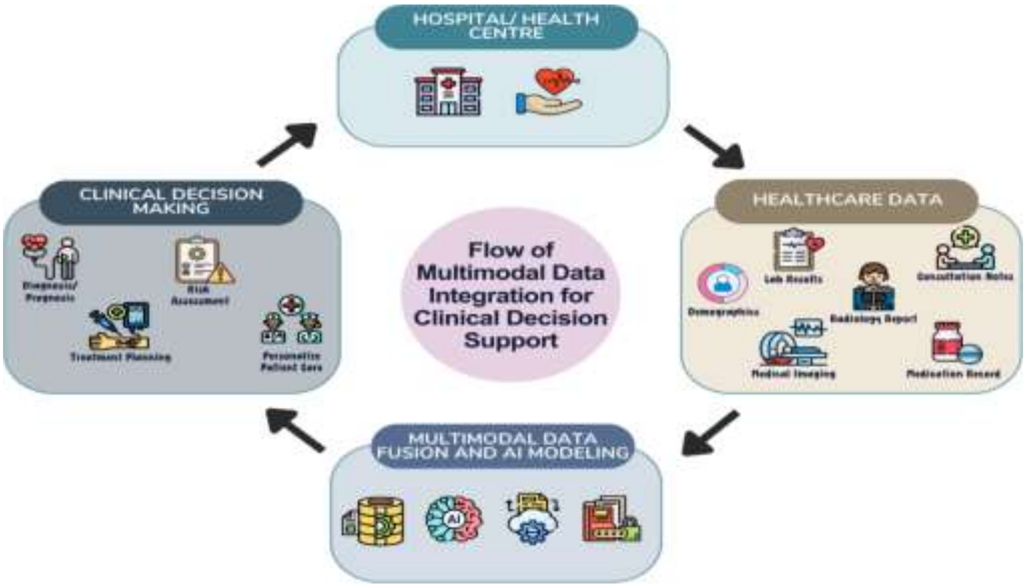

Figure 2. *Multimodal Data Fusion Pipeline for Personalized Cancer Care*

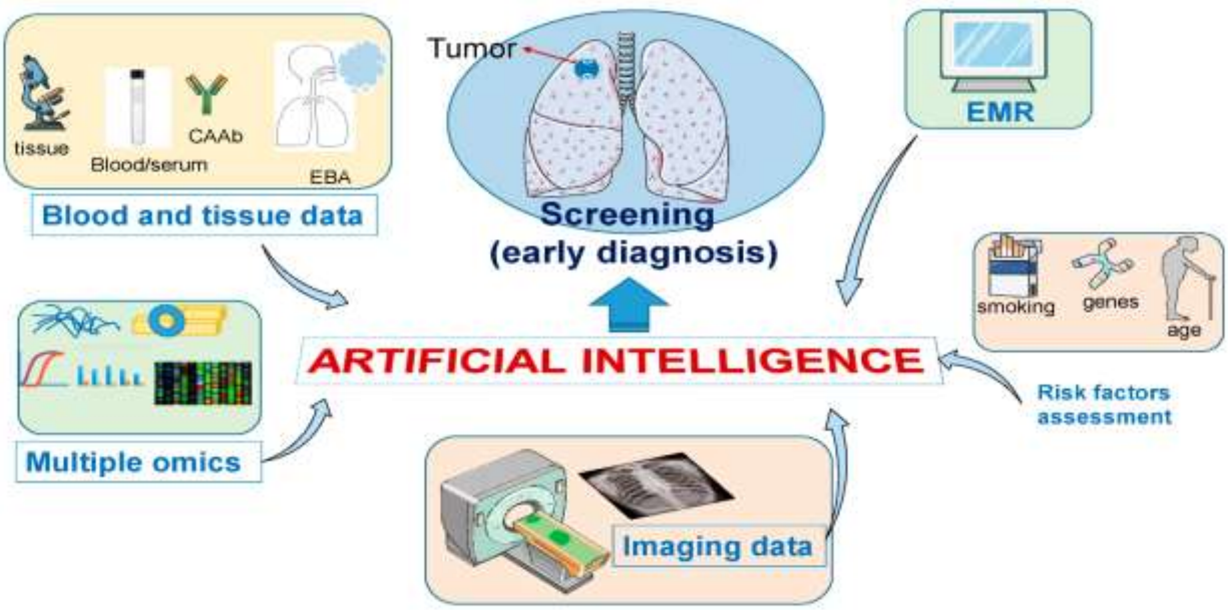

Figure 3. *AI-Enabled Medical Imaging Workflow for Cancer Diagnosis*

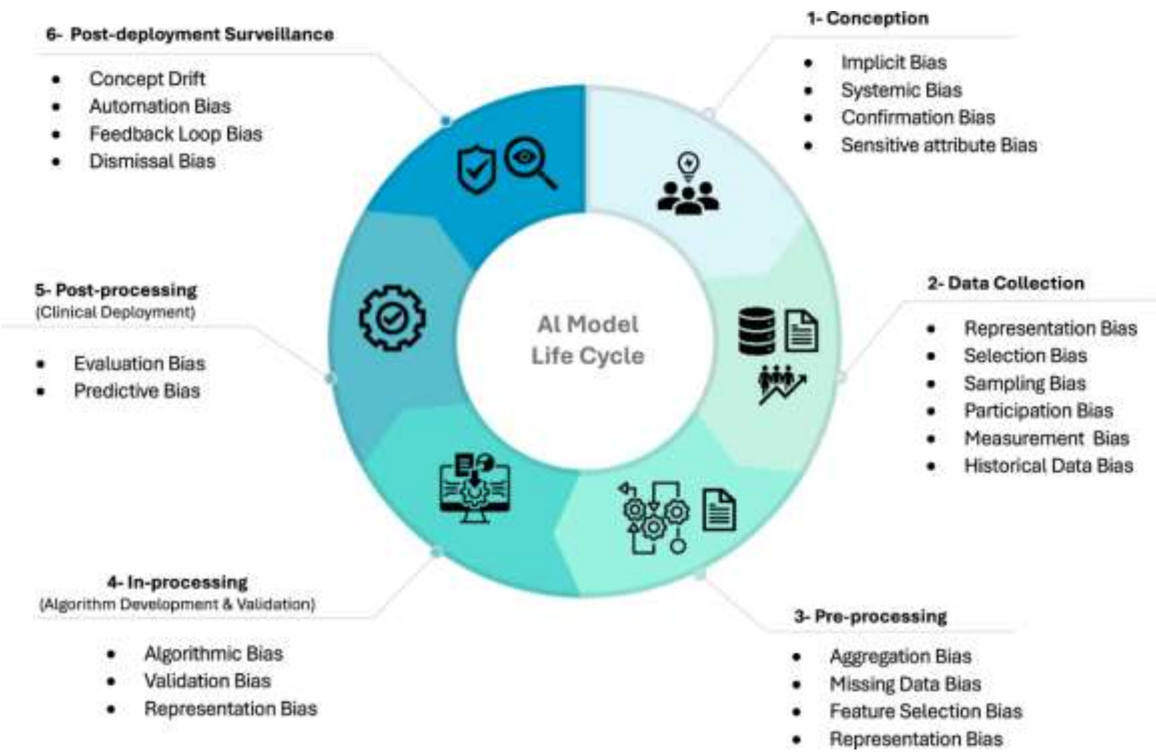

Figure 5. *Ethical, Explainable AI, and Governance Framework*

6. Limitations

Several limitations exist with this study. First, it is conceptually based on a synthesis of relevant literature as opposed to empirically focused documentation from primary experimentation, which may reduce the ability to directly quantitatively compare the models. Second, information on environmental exposures often goes on proxies of exposure and population-level indicators, which might not capture the full extent of variability of individual exposures. Third, many AI models reviewed are still in early phases in clinical validation, and more prospective and multi-center studies are needed.

7. Future Research Directions

Future research needs to focus on large-scale clinical validation of environment-informed precision oncology using diverse populations and healthcare systems. The development of federated learning and privacy-preserving analytics provides promising opportunities for secure data integration. The incorporation of real-time monitoring of the surrounding environment, wearable sensors, and self-reported outcomes may further enhance the predictive accuracy and personalization. Interdisciplinary studies of the ethical, legal, and social implications will continue to be a crucial part of ensuring ethical and responsible innovation.

8. Conclusion

This study aims to present a comprehensive AI-driven big data framework of environmentally informed personalized cancer treatment that incorporates clinical data, multi-omics profiles, AI-enabled medical imaging, and exposomics intelligence. The results show that incorporating environmental science into precision oncology enhances the diagnosis, risk stratification, and treatment individualization and promotes preventive and equitable care for cancer. As the pace of technological development in artificial intelligence, environmental informatics, and biomedical technologies continues to increase, interdisciplinary collaboration and ethical governance will be key to the continued realization of the potential of environmental precision oncology. Ultimately, big data analytics using AI is not only a small step in the right direction but rather reflects a paradigm shift towards data-centered, patient-specific, and environmentally responsive cancer care.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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