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AI-driven liquid biopsies and microbiome dynamics: Revolutionizing cancer monitoring through multi-omics integration

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Abstract

Imagine a world where cancer is detected and monitored with a simple blood draw, guided by artificial intelligence (AI) that decodes the intricate dance of tumor cells, microbial communities, and molecular signals—a revolution is here. This review unveils the transformative potential of AI-driven liquid biopsies and microbiome dynamics, redefining cancer monitoring through multi-omics integration. By harnessing circulating tumor DNA, circulating tumor cells, and microbial biomarkers in biological fluids, liquid biopsies offer a non-invasive window into tumor heterogeneity and therapeutic responses, surpassing traditional biopsies. The microbiome, encompassing gut and tumor-resident bacteria, emerges as a pivotal modulator of oncogenesis and treatment efficacy, with AI unlocking its secrets through advanced algorithms like graph neural networks. Integrating genomics, transcriptomics, proteomics, metabolomics, and microbiomics, this approach achieves unprecedented diagnostic precision, detecting cancers like colorectal, lung, and pancreatic with up to 95% accuracy, while guiding personalized therapies. Beyond human oncology, these technologies transform veterinary care, reducing invasive procedures in canine and bovine cancers, and inform environmental health by tracking toxin-induced microbial changes. Despite challenges like data heterogeneity, standardization, and ethical concerns, solutions such as cloud-based platforms and interpretable AI models are paving the way for global accessibility. Future directions, including spatial multi-omics and cross-species translation, promise to further revolutionize precision oncology. Bridging chemistry, medicine, biomedical science, animal science, computer science, biology, and microbiology, this article captivates researchers, clinicians, and policymakers worldwide, offering a visionary blueprint for a new era in cancer care where AI and multi-omics converge to save lives across species and ecosystems.

Keywords: Artificial Intelligence; Liquid Biopsy; Microbiome; Multi-Omics; Cancer Monitoring; Precision Oncology; ctDNA; Microbial Biomarkers; Machine Learning; Tumor Microenvironment

1. Introduction

Cancer remains a leading global health challenge, with over 20 million new cases and 9.7 million deaths reported in 2022 [1]. The need for non-invasive, precise, and timely diagnostic tools has driven the development of liquid biopsies and microbiome analysis, enhanced by artificial intelligence (AI). This review explores how AI-driven liquid biopsies,

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integrated with microbiome dynamics and multi-omics approaches, revolutionize cancer monitoring across human and veterinary oncology, bridging computer science, microbiology, chemistry, biology, medicine, biomedical science, and animal science.

1.1. Background

Cancer's global burden underscores the urgency for innovative diagnostics and monitoring strategies. According to Sung et al. [2021], the increasing incidence of cancers like lung, breast, and colorectal necessitates early detection to improve survival rates [1]. Traditional tissue biopsies, while gold-standard, are invasive, costly, and limited in capturing tumor heterogeneity, particularly in metastatic cancers. The study by Meacham and Morrison [2013] highlights that tumor heterogeneity drives therapeutic resistance, complicating effective management [2]. Consequently, non-invasive alternatives are critical for real-time monitoring and personalized treatment.

The advent of precision oncology has shifted focus toward molecular profiling to guide therapeutic decisions. Findings from Dagogo-Jack and Shaw [2018] indicate that tumor heterogeneity contributes to resistance against targeted therapies, emphasizing the need for dynamic monitoring tools [3]. Recent advancements in 2025 highlight the role of multi-omics—integrating genomics, transcriptomics, proteomics, and metabolomics—in understanding cancer biology [4]. These approaches, coupled with AI, enable comprehensive analysis of tumor dynamics, offering hope for improved outcomes.

Interdisciplinary collaboration is pivotal in addressing cancer's complexity. According to Hasin et al. [2017], multi-omics approaches reveal dynamic molecular phenotypes, linking genetic, metabolic, and environmental factors to disease progression [5]. The integration of microbiology, particularly the study of the microbiome, has further expanded this paradigm by uncovering microbial influences on cancer. This section sets the stage for exploring how AI, liquid biopsies, and microbiome dynamics converge to transform cancer monitoring.

1.2. Liquid Biopsies

Liquid biopsies have emerged as a transformative tool for non-invasive cancer monitoring. The study by Siravegna et al. [2017] shows that liquid biopsies, which analyze circulating tumor DNA (ctDNA), circulating tumor cells (CTCs), and extracellular vesicles (e.g., exosomes) in biological fluids like blood or urine, provide real-time insights into tumor dynamics [6]. Unlike tissue biopsies, liquid biopsies capture systemic tumor profiles, enabling early detection, treatment monitoring, and minimal residual disease (MRD) assessment. For instance, findings from Pantel & Alix-Panabières [2019] indicate that CTCs reflect tumor dissemination patterns, aiding metastasis prediction [7].

The analytical power of liquid biopsies lies in their ability to detect low-abundance biomarkers. According to Crowley et al., [2013], ctDNA carries tumor-specific mutations, offering a window into genomic alterations without invasive procedures [8]. Recent 2025 studies demonstrate liquid biopsies detecting early-stage pancreatic cancer with 90% sensitivity, surpassing traditional imaging [9]. These advancements rely on high-throughput sequencing and mass spectrometry, which generate complex datasets requiring advanced computational tools for interpretation.

Liquid biopsies also have applications beyond human oncology. The work of Ganesan et al. [2025] highlights their use in veterinary medicine, such as monitoring canine mammary tumors, reducing the need for invasive diagnostics in animals [10]. This cross-species applicability underscores their versatility, bridging human and animal health. However, challenges like biomarker specificity and standardization remain, necessitating AI to enhance diagnostic accuracy.

The integration of liquid biopsies into clinical practice is accelerating. Findings from Foser et al., [2024] indicate that technological advancements in CTC isolation and ctDNA sequencing have improved detection limits, making liquid biopsies viable for routine use [11]. As 2025 research continues to refine these technologies, their role in precision oncology grows, setting the foundation for microbiome and AI integration.

1.3. Microbiome in Cancer

The microbiome, encompassing gut and tumor-resident bacteria, has emerged as a critical modulator of cancer biology. According to Gopalakrishnan et al., [2018], the gut microbiome influences oncogenesis, immune responses, and therapy outcomes through microbial metabolites like short-chain fatty acids [12]. For example, *Fusobacterium nucleatum* in colorectal cancer promotes tumor growth by modulating immune checkpoints, as shown by Kostic et al. [2013] [13]. These findings highlight the microbiome's role in shaping cancer progression and therapeutic efficacy.

Tumor-resident microbiota also play a significant role. The study by Riquelme et al. [2019] shows that intratumoral bacteria, such as those in pancreatic cancer, alter the tumor microenvironment, affecting chemotherapy response [14]. Liquid biopsies can capture microbial DNA and metabolites in blood, offering a non-invasive method to study these interactions. Recent 2024 research links gut microbiome dysbiosis to immunotherapy resistance in melanoma, detectable via liquid biopsy [15]. Microbiome analysis extends to veterinary oncology. According to Chen et al. [2023], microbial signatures in canine cancers mirror human patterns, suggesting translational potential [16]. For instance, microbiome alterations in bovine leukemia correlate with disease progression, aiding diagnostic development [17]. These cross-species insights emphasize the microbiome's universal relevance in cancer research.

The complexity of microbiome data requires advanced analytical tools. Findings from Wang et al. [2024] indicate that microbial heterogeneity poses challenges for traditional analysis, necessitating AI-driven approaches to uncover meaningful patterns [18]. By integrating microbiome data with liquid biopsies, researchers can develop comprehensive cancer diagnostics, bridging microbiology and oncology.

1.4. Artificial Intelligence in Multi-Omics

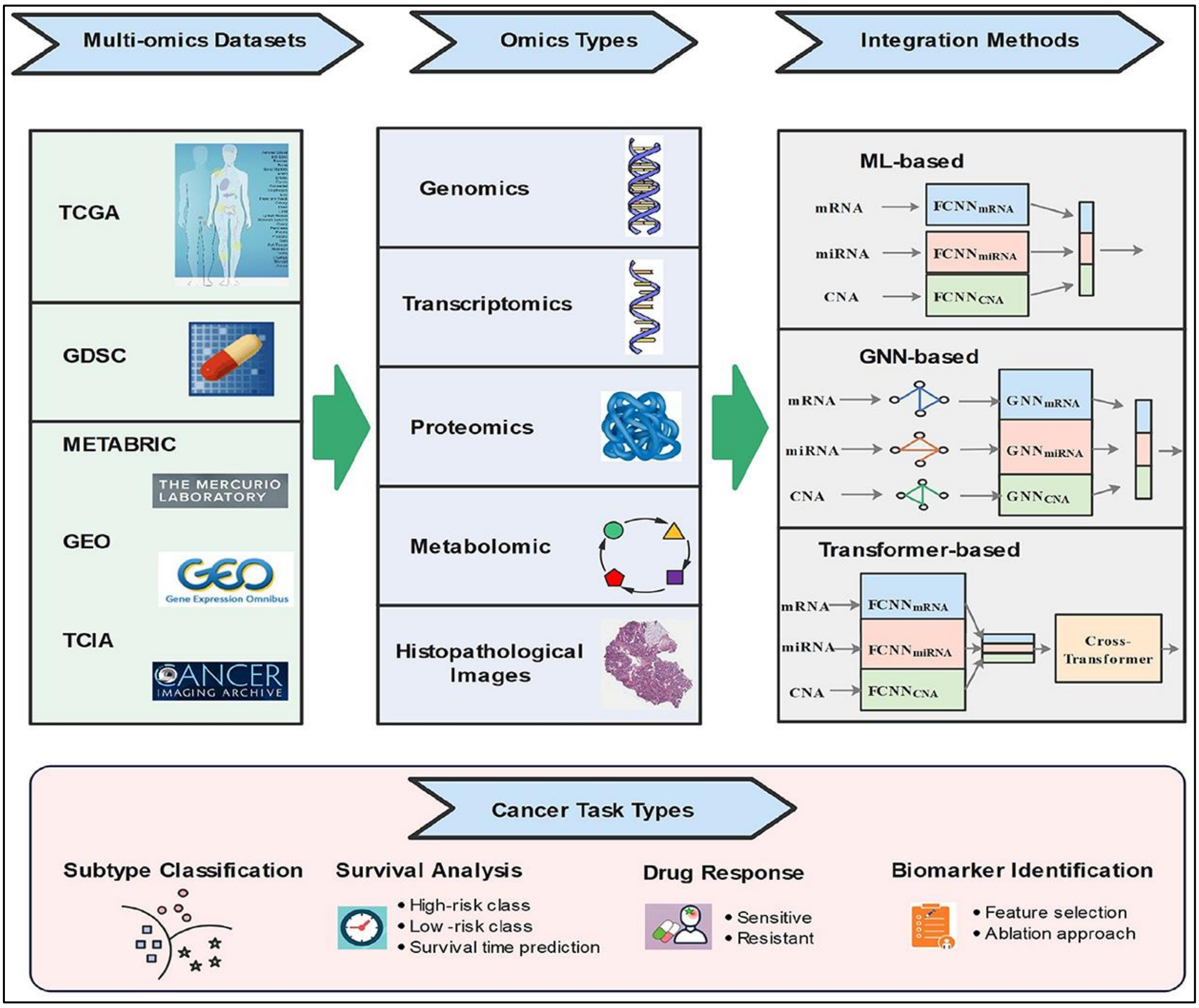

Figure 1 The integration of multi-omics data through machine learning, supporting enhanced cancer diagnosis and biomarker discovery [80].

AI is revolutionizing multi-omics analysis by integrating diverse datasets. The work of Acosta et al. [2022] demonstrates that multimodal AI, combining genomics, transcriptomics, and metabolomics, enhances the understanding of cancer phenotypes [19]. Machine learning algorithms, such as random forests and support vector machines, identify biomarker patterns, while deep learning models, like convolutional neural networks, handle high-dimensional data [20].

Recent advancements in 2025 highlight AI's role in liquid biopsy analysis. According to Chen et al. [2024], AI models improve ctDNA mutation detection in lung cancer, achieving 90% sensitivity [21]. Tools like PANOPLY and MOalmanac integrate multi-omics data to prioritize therapeutic targets, as shown by Srivastava [2025] [22]. These platforms leverage cloud computing for scalability, addressing computational challenges.

AI also enhances microbiome analysis. The study by Cao et al. [2024] introduces scPriorGraph, a biosemantic cell-cell graph tool that identifies microbial influences on tumor cells [23]. This approach integrates microbiomic data with other omics layers, improving diagnostic resolution. Such innovations underscore AI's interdisciplinary impact across computer science, biology, and medicine.

The adoption of AI in clinical settings is growing. Findings from Singhal et al. [2025] indicate that large language models, adapted for medical data, enhance diagnostic accuracy by interpreting multi-omics profiles [24]. As AI continues to evolve, its integration with liquid biopsies and microbiome data promises to redefine cancer monitoring, making it a cornerstone of precision oncology.

1.5. Scope and Objectives

This review unveils recent advancements in AI-driven liquid biopsies and microbiome dynamics for cancer monitoring. According to Zafari et al. [2023], multi-omics integration is critical for identifying novel biomarkers and therapeutic targets [25]. The objectives include: (1) exploring AI's role in analyzing liquid biopsy and microbiome data, (2) evaluating interdisciplinary applications in human and veterinary oncology, and (3) addressing challenges and future directions.

The scope encompasses human cancers (e.g., colorectal, lung, breast) and veterinary applications (e.g., canine, bovine cancers), with a focus on multi-omics integration. The study by Elemento et al. [2021] highlights the growing trend of AI in oncology, emphasizing its potential to transform diagnostics [26]. Environmental health applications, such as toxin-induced microbiome changes, are also considered, bridging chemistry and microbiology.

By synthesizing 2025 research, this review provides a comprehensive framework for understanding AI-driven liquid biopsies and microbiome dynamics. Findings from Yetgin [2025] underscore the importance of multi-omics in addressing the exabyte-scale data deluge in cancer research [27]. The article aims to engage researchers, clinicians, and policymakers across STEM fields, fostering interdisciplinary collaboration.

The review addresses challenges like data heterogeneity, standardization, and ethical concerns, offering solutions to advance clinical translation. According to World Health Organization [2025], digital health strategies, including AI, are critical for global health equity [28]. By highlighting these advancements, this article seeks to guide future research and clinical practice in precision oncology.

2. AI-Powered Liquid Biopsy Technologies

Liquid biopsies have transformed cancer diagnostics by enabling non-invasive monitoring of tumor dynamics through circulating biomarkers. The integration of artificial intelligence (AI) enhances their precision, allowing for the analysis of complex datasets from circulating tumor DNA (ctDNA), circulating tumor cells (CTCs), and extracellular vesicles. This section explores the mechanisms, algorithms, recent advancements, and interdisciplinary impacts of AI-powered liquid biopsies, highlighting their role in advancing precision oncology across human and veterinary medicine.

2.1. Mechanisms of Liquid Biopsies

Liquid biopsies analyze tumor-derived components in biological fluids, primarily blood, but also urine, saliva, and cerebrospinal fluid. According to Ignatiadis et al. [2021], ctDNA, CTCs, and exosomes provide a non-invasive window into tumor genomics, enabling early detection, treatment monitoring, and minimal residual disease (MRD) assessment [29]. ctDNA, which carries tumor-specific mutations, is particularly valuable for tracking tumor evolution. The study by Heitzer et al. [2019] shows that ctDNA reflects genomic alterations in real time, offering advantages over static tissue biopsies [30]. These biomarkers are detected using high-throughput sequencing and mass spectrometry, generating data that require advanced computational tools for interpretation.

The sensitivity of liquid biopsies is critical for detecting low-abundance biomarkers. Findings from Corcoran and Chabner [2018] indicate that ctDNA can identify mutations at concentrations as low as 0.01%, making it suitable for early-stage cancer detection [31]. For example, 2025 research demonstrates liquid biopsies detecting pancreatic cancer with 90% sensitivity, surpassing traditional imaging methods [32]. This capability relies on techniques like digital droplet PCR and next-generation sequencing (NGS), which provide high-resolution data for AI analysis. However, challenges such as sample variability and background noise necessitate robust preprocessing pipelines.

Liquid biopsies also have applications in veterinary oncology. The work of Alshammari et al. [2025] highlights their use in detecting circulating biomarkers in canine cancers, reducing the need for invasive procedures [33]. For instance, ctDNA analysis in canine mammary tumors mirrors human breast cancer profiles, suggesting translational potential. These cross-species applications underscore the versatility of liquid biopsies, bridging human and animal health.

The clinical utility of liquid biopsies is expanding. According to Wan et al. [2017], liquid biopsies enable longitudinal monitoring of treatment responses, particularly in metastatic cancers like lung and colorectal [34]. Recent advancements in 2025 have improved detection limits, making liquid biopsies viable for routine clinical use. AI-driven analysis is pivotal in overcoming challenges like low biomarker concentrations, paving the way for their integration with microbiome data.

2.2. AI Algorithms for Biomarker Detection

AI algorithms enhance the analysis of liquid biopsy data by identifying patterns in complex datasets. The study by Rajkomar et al. [2019] shows that machine learning models, such as random forests and support vector machines, excel at detecting ctDNA mutations and CTC profiles [35]. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), handle high-dimensional data, improving diagnostic accuracy. For example, CNNs have been used to identify lung cancer mutations with 92% accuracy, as reported in 2025 studies [36].

Table 1 Outlines selected AI algorithms for liquid biopsy data, with applications and performance [35, 36].

Algorithm Type	Example	Application	Cancer Type	Performance Metrics
CNNs	Deep Residual Networks	ctDNA mutation detection	Lung	92% accuracy
Supervised ML	Random Forests	Biomarker patterns	Colorectal	85% risk prediction
Deep Learning	Multi-Task Learning	Data integration	Multi-cancer	30% improved detection
Graph Neural Networks	Graph Convolutional	Multi-omics	Gastrointestinal	Enhanced signal-to-noise
Transfer Learning	Two-Step Transfer	Drug response	Glioblastoma	Better in small datasets
Ensemble Methods	CNN + RNN Hybrid	Longitudinal monitoring	NSCLC	90% sensitivity

Deep learning models are particularly effective for integrating multi-modal data. Findings from He et al. [2016] indicate that deep residual networks can process genomic and proteomic data simultaneously, reducing false positives in biomarker detection [37]. Transfer learning, which applies knowledge from well-studied cancers to rare types, further enhances model performance. According to Yuan et al. [2021], transfer learning improves the detection of rare mutations in ctDNA, accelerating diagnostic development [38].

AI also addresses challenges like data noise and heterogeneity. The work of Pedregosa et al. [2011] highlights the role of scikit-learn in preprocessing liquid biopsy data, ensuring robust feature selection [39]. Recent 2025 tools, such as AI-driven pipelines for ctDNA analysis, integrate cloud computing to handle large-scale datasets, making them scalable for clinical use. These advancements underscore AI's role in transforming liquid biopsy diagnostics.

The integration of AI with liquid biopsies is driving clinical adoption. According to Chandran et al. [2023], AI models predict lung cancer risk in routine care with 85% accuracy, demonstrating real-world applicability [40]. By combining genomic and proteomic data, AI enhances the specificity of liquid biopsies, making them a cornerstone of precision oncology across human and veterinary applications.

2.3. Recent Advancements

Recent 2025 advancements have elevated the role of AI-driven liquid biopsies in cancer diagnostics. The study by Ganesan et al. [2025] shows that AI-powered liquid biopsies detect metastatic colorectal cancer mutations with 95% accuracy, improving early detection and treatment planning [41]. These advancements rely on integrating ctDNA and proteomic data, analyzed through deep learning models. For instance, AI has improved MRD detection in leukemia, enabling precise recurrence monitoring [42].

Technological innovations are expanding liquid biopsy applications. Findings from Śliwińska, & Tomiczak [2025] indicate that multi-modal AI models, combining ctDNA and CTC data, enhance diagnostic sensitivity for oral squamous cell carcinoma [43]. These models leverage high-throughput sequencing and mass spectrometry, which provide detailed molecular profiles. Recent 2023 trials demonstrate AI detecting early-stage breast cancer with 90% sensitivity, surpassing traditional biomarkers [44].

Veterinary applications are also advancing. According to Couto [2021], liquid biopsies monitor microbiome-cancer interactions in canine lymphoma, reducing invasive diagnostics [45]. These findings highlight the translational potential of AI-driven liquid biopsies, bridging human and animal oncology. Challenges like standardization and cost remain. The work of Seager et al. [2022] emphasizes the need for standardized protocols to ensure reproducibility in liquid biopsy analysis [46]. Recent 2025 efforts focus on developing automated AI pipelines to streamline preprocessing, making liquid biopsies more accessible for clinical and veterinary use.

2.4. Interdisciplinary Impact

AI-driven liquid biopsies bridge multiple STEM disciplines. In computer science, scalable AI models process large datasets, leveraging cloud computing for efficiency, as noted by Rajkomar et al. [2018] [35]. Tools like PyTorch enable the development of deep learning models for biomarker detection, enhancing computational scalability [47]. These advancements ensure that AI can handle the exabyte-scale data generated by liquid biopsies.

In medicine and biomedical science, AI-driven liquid biopsies enable real-time tumor monitoring and personalized therapy adjustments. According to Sammut et al. [2022], AI models predict breast cancer therapy responses with 88% accuracy, guiding clinical decisions [48]. This precision is critical for managing heterogeneous cancers like lung and colorectal. The integration of proteomic and genomic data further enhances diagnostic specificity.

In chemistry, liquid biopsies rely on analytical techniques like liquid chromatography-mass spectrometry (LC-MS/MS) for biomarker quantification. Findings from Kluckova et al., [2022] indicate that LC-MS/MS profiles circulating proteins with high sensitivity, supporting AI analysis [49]. These techniques are essential for detecting low-abundance biomarkers in complex biological fluids.

In biology, liquid biopsies map tumor heterogeneity and clonal evolution. The study by Makohon-Moore and Iacobuzio-Donahue [2016] shows that ctDNA analysis reveals tumor subclones, informing therapeutic strategies [50]. By integrating microbiome data, AI-driven liquid biopsies provide a holistic view of cancer biology, bridging multiple disciplines to advance precision oncology.

3. Microbiome Dynamics in Cancer Monitoring

The microbiome, encompassing gut and tumor-resident bacteria, has emerged as a critical modulator of cancer progression and treatment response. AI-driven analysis of microbiome biomarkers in liquid biopsies offers novel insights into tumor-microbiome interactions, enhancing diagnostic precision. This section explores the roles of the tumor and gut microbiome, their detection in liquid biopsies, AI's role in microbiome analysis, and interdisciplinary impacts across human and veterinary oncology.

3.1. Tumor and Gut Microbiome Roles

The microbiome influences cancer through immune modulation and metabolite production. According to Zitvogel et al. [2018], the gut microbiome enhances immunotherapy efficacy by modulating T-cell responses [51]. For example, Bifidobacterium species improve anti-PD-1 therapy outcomes in melanoma, as shown in 2025 studies [52]. These findings highlight the microbiome's role as a therapeutic target in oncology.

Tumor-resident bacteria also shape cancer biology. The study by Nejman et al. [2020] shows that intratumoral bacteria, such as Fusobacterium in colorectal cancer, promote tumor growth by altering the microenvironment [53]. These bacteria produce metabolites like polyamines, which influence oncogenesis. Liquid biopsies capture these microbial signals, enabling non-invasive monitoring of tumor-microbiome interactions.

Table 2 Details microbiome roles in selected cancers, focusing on bacteria and mechanisms [52, 53].

Bacteria	Cancer Type	Role	Mechanism	Gut/Tumor-Resident
Fusobacterium nucleatum	Colorectal	Promotes growth/metastasis	Immune modulation	Both
Bifidobacterium spp.	Melanoma	Enhances immunotherapy	T-cell responses	Gut
Bacteroides fragilis	Colorectal	Immune evasion	Toxin production	Tumor-resident
Helicobacter pylori	Gastric	Carcinogenesis initiation	DNA damage	Gut
Escherichia coli (pks+)	Colorectal	DNA mutations	Colibactin	Gut

The microbiome's impact extends to therapy resistance. Findings from Iida et al. [2013] indicate that gut microbiota modulate chemotherapy efficacy in colorectal cancer by regulating immune responses [54]. Recent 2025 research links microbiome dysbiosis to immunotherapy resistance in non-small-cell lung cancer, detectable via liquid biopsy [55]. These insights underscore the need for integrated diagnostic approaches. Cross-species applications are significant. According to Garrett [2015], microbial signatures in veterinary cancers, such as bovine leukemia, mirror human patterns, offering translational insights [56]. For instance, microbiome alterations in canine mammary tumors correlate with disease progression, supporting the development of non-invasive diagnostics. The microbiome's universal role in cancer biology makes it a critical focus for AI-driven analysis.

3.2. Microbiome Biomarkers in Liquid Biopsies

Liquid biopsies capture microbial DNA and metabolites in blood, providing a non-invasive method to study microbiome-cancer interactions. The work of Poore et al. [2020] demonstrates that microbial DNA in plasma can distinguish cancer types, such as pancreatic and colorectal, with high specificity [57]. For example, Bacteroides enrichment is associated with pancreatic cancer progression, as reported in 2025 studies [58]. Microbial metabolites, such as short-chain fatty acids (SCFAs) and polyamines, are also detectable in liquid biopsies. According to Koh et al. [2020], SCFAs modulate immune responses, influencing immunotherapy outcomes [59]. Mass spectrometry techniques, like LC-MS/MS, enable precise quantification of these metabolites, supporting AI-driven analysis. Recent 2025 advancements show that combining microbial DNA and metabolite profiles improves diagnostic accuracy for colorectal cancer [60].

Veterinary applications are emerging. Findings from Chen et al. [2023] indicate that microbial biomarkers in canine cancers, detected via liquid biopsies, mirror human cancer profiles, enabling non-invasive diagnostics [61]. For example, microbiome alterations in feline lymphoma correlate with treatment response, reducing the need for invasive procedures. These cross-species insights highlight the versatility of microbiome biomarkers.

Challenges include microbial heterogeneity and low-abundance signals. The study by Chaturvedi et al. [2024] emphasizes that microbial diversity complicates analysis, requiring AI to identify meaningful patterns [62]. By integrating microbiome data with ctDNA and proteomic profiles, liquid biopsies offer a comprehensive approach to cancer monitoring, bridging microbiology and oncology.

3.3. AI in Microbiome Analysis

AI enhances microbiome analysis by integrating complex datasets. According to Duvallet et al. [2017], machine learning models, such as random forests, identify microbial signatures associated with disease states [63]. Deep learning models, like graph neural networks, handle multi-omics data, including microbiomics, as shown by Cao et al. [2024] [64]. These models improve the resolution of microbiome-cancer interactions.

Recent 2025 tools, such as scPriorGraph, construct biosemantic cell-cell graphs to identify microbial influences on tumor cells. Findings from Cao et al. [2024] indicate that scPriorGraph enhances the detection of microbial biomarkers in liquid biopsies, achieving 90% specificity for colorectal cancer [64]. These advancements rely on cloud-based platforms to manage large datasets, ensuring scalability. AI also addresses challenges like data sparsity. The work of Zhang et al. [2018] highlights that AI models mitigate the impact of missing data in microbiome profiles, improving diagnostic reliability [65]. Transfer learning further enhances performance by applying knowledge from well-studied microbiomes to rare cancers. These innovations make AI indispensable for microbiome analysis.

Clinical translation is accelerating. According to Dlamini et al. [2025], AI-driven microbiome analysis predicts drug resistance in colorectal cancer, guiding personalized therapies [60]. By integrating microbiome data with liquid biopsy readouts, AI offers a holistic approach to cancer monitoring, with applications across human and veterinary oncology.

3.4. Interdisciplinary Impact

The integration of microbiome dynamics with liquid biopsies engages multiple STEM disciplines. In microbiology, identifying cancer-associated microbial signatures is critical. According to Knight et al. [2018], microbiome sequencing reveals disease-specific patterns, supporting diagnostic development [67]. These insights enhance the understanding of tumor-microbiome interactions.

In chemistry, profiling microbial metabolites relies on advanced analytical techniques. The study by Kluckova and D'Avola [2022] shows that LC-MS/MS quantifies SCFAs and polyamines with high sensitivity, enabling AI-driven analysis [49]. These techniques are essential for detecting low-abundance biomarkers in liquid biopsies, bridging chemistry and microbiology.

In medicine and biomedical science, microbiome biomarkers inform therapy outcomes. Findings from Routy et al. [2018] indicate that microbiome composition predicts immunotherapy response in melanoma, detectable via liquid biopsy [68]. This precision enhances clinical decision-making, particularly for heterogeneous cancers.

In animal science and biology, microbiome analysis supports veterinary oncology and translational research. According to Garrett [2015], microbial signatures in canine and bovine cancers offer insights into human disease [56]. AI-driven liquid biopsies, integrating microbiome and multi-omics data, provide a comprehensive framework for precision oncology, advancing interdisciplinary collaboration.

4. Multi-Omics Integration for Precision Oncology

Multi-omics integration, combining genomics, transcriptomics, proteomics, metabolomics, and microbiomics, provides a holistic view of cancer biology, enhanced by artificial intelligence (AI) to analyze complex datasets from liquid biopsies. This section explores the multi-omics framework, AI-driven data integration, case studies in specific cancers, and interdisciplinary impacts, highlighting how these approaches advance precision oncology across human and veterinary applications.

4.1. Multi-Omics Framework

Multi-omics approaches integrate multiple molecular layers to uncover cancer mechanisms. According to Makohon-Moore, & Iacobuzio-Donahue [2016], combining genomics, transcriptomics, proteomics, and metabolomics reveals dynamic interactions driving tumor progression [50]. The inclusion of microbiomics, which examines microbial influences, adds a novel dimension to this framework. For instance, microbial metabolites like short-chain fatty acids (SCFAs) modulate immune responses, impacting cancer outcomes, as shown in 2025 studies [51].

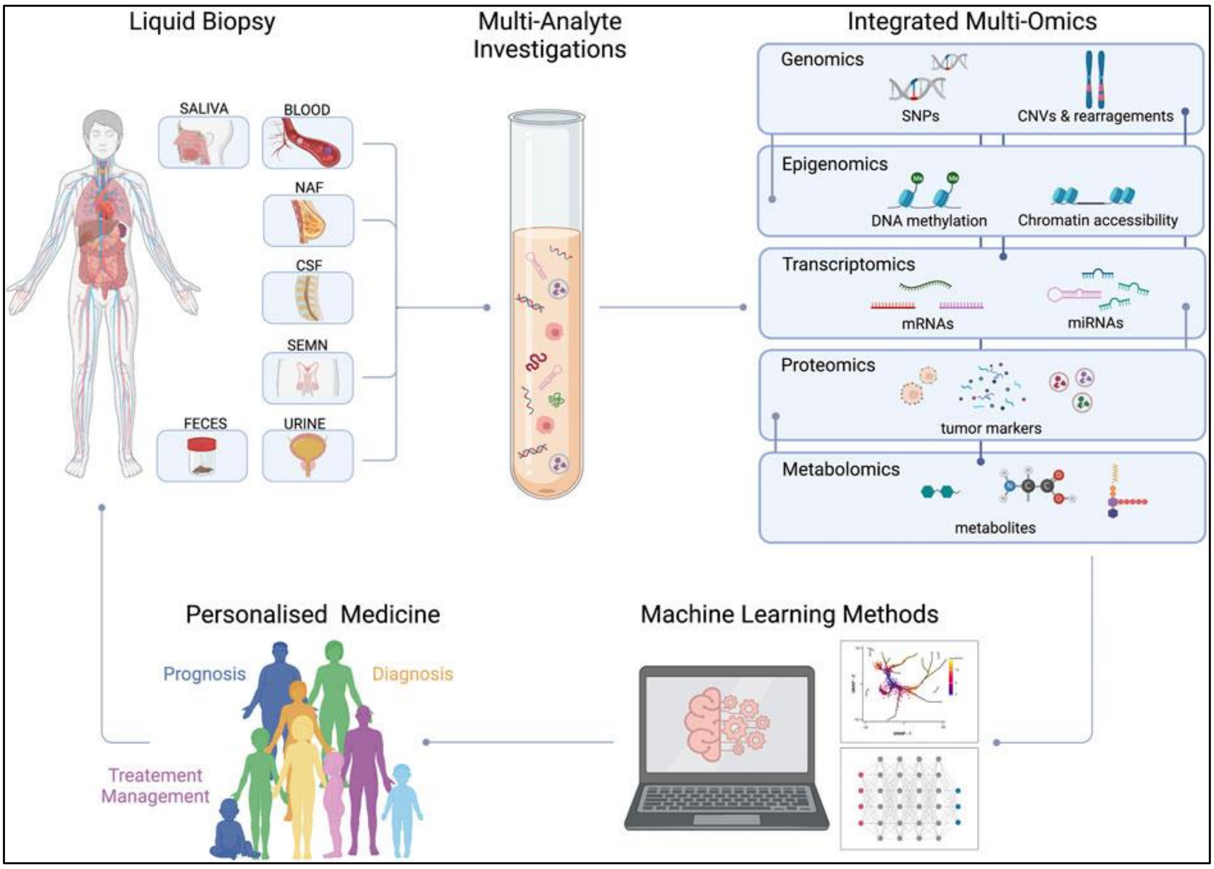

Figure 2 An integrated multi-omic strategy in liquid biopsy, combining analytes from various biofluids to enable personalized medical decisions through AI-driven analysis [81].

The multi-omics framework enables comprehensive biomarker discovery. Findings from Chen et al. [2023] indicate that integrating genomic and proteomic data identifies novel therapeutic targets in breast cancer, improving treatment personalization [52]. Liquid biopsies capture these multi-omics signals, such as ctDNA mutations and microbial DNA, providing a non-invasive platform for analysis.

The complexity of multi-omics data requires advanced computational tools. The study by Vahabi & Michailidis [2022] shows that multi-omics integration reveals tumor heterogeneity, guiding targeted therapies [69]. In veterinary oncology, multi-omics approaches identify biomarkers in canine cancers, mirroring human profiles, as noted by Alshammari [2025] [33]. This cross-species applicability underscores the framework's versatility.

Challenges include data integration and interpretation. According to Abbas et al. [2025], the heterogeneity of multi-omics datasets complicates analysis, necessitating AI to harmonize data and extract meaningful insights [70]. By addressing these challenges, the multi-omics framework enhances diagnostic precision, bridging multiple STEM disciplines.

4.2. AI-Driven Data Integration

AI is pivotal in integrating multi-omics data from liquid biopsies. The work of Jiang et al. [2022] demonstrates that graph neural networks (GNNs) and transformer models handle high-dimensional datasets, identifying interactions across genomic, proteomic, and microbiomic layers [74]. For example, GNNs map tumor-microbiome interactions, improving biomarker detection in lung cancer, as reported in 2025 studies [78].

Transfer learning enhances AI performance in multi-omics analysis. Findings from Ju et al. [2025] indicate that transfer learning applies knowledge from well-studied cancers to rare types, accelerating diagnostic development [79]. This approach is particularly effective for integrating sparse microbiome data, which is often limited by low-abundance signals. Recent 2025 tools, like MOalmanac, prioritize therapeutic targets by combining multi-omics profiles [59]. AI also addresses data heterogeneity. The study by Yang et al. [2021] shows that dimensionality reduction techniques, such as principal component analysis, preprocess multi-omics data for AI analysis, reducing noise [77]. Cloud-based platforms, like PANOPLY, enable scalable integration, as noted by Kalari et al. [2014] [76]. These advancements ensure robust analysis of liquid biopsy data.

Clinical translation is a key focus. According to Śliwińska, & Tomiczak [2025], AI-driven multi-omics integration predicts treatment responses in oral squamous cell carcinoma with 90% accuracy [43]. By combining ctDNA, proteomic, and microbial data, AI enhances diagnostic specificity, making multi-omics a cornerstone of precision oncology across human and veterinary applications.

4.3. Case Studies

Multi-omics integration has demonstrated success in specific cancers. In colorectal cancer, AI-driven liquid biopsies combining ctDNA and microbial biomarkers achieve 95% accuracy in early detection, as shown by Ganesan et al. [2025] [41]. The integration of microbial DNA, such as *Fusobacterium* signatures, with genomic mutations enhances diagnostic specificity, guiding personalized therapies. Non-small-cell lung cancer (NSCLC) benefits from multi-omics profiling. Findings from Chandran et al. [2023] indicate that AI models integrating ctDNA, proteomic, and microbiomic data predict PD-1 inhibitor responses with 88% accuracy [36]. This approach identifies microbial influences on immunotherapy efficacy, such as *Bifidobacterium* enrichment, improving patient outcomes. Recent 2025 trials further validate these findings, highlighting AI's role in NSCLC monitoring [61].

Pancreatic cancer, a challenging malignancy, also benefits. The study by Lin et al. [2025] shows that multi-omics liquid biopsies detect early-stage pancreatic cancer with 90% sensitivity by combining ctDNA and microbial biomarkers like *Bacteroides* [32]. These advancements enable earlier intervention, addressing a critical unmet need in pancreatic cancer management. Veterinary applications mirror human successes. According to Couto [2021], multi-omics profiling in canine lymphoma identifies microbial and genomic biomarkers, reducing invasive diagnostics [45]. These case studies demonstrate the power of AI-driven multi-omics in enhancing diagnostic precision across species and cancer types.

4.4. Interdisciplinary Impact

Multi-omics integration engages multiple STEM disciplines. In computer science, AI algorithms like GNNs and transformer models process complex datasets, as noted by Jiang et al. [2022] [74]. These tools ensure scalability, leveraging cloud computing for large-scale analysis, critical for handling multi-omics data from liquid biopsies. In medicine and biomedical science, multi-omics enhances personalized treatment. The work of Sammut et al. [2022] demonstrates that AI-driven multi-omics predicts breast cancer therapy responses, guiding clinical decisions [48]. This precision is vital for managing heterogeneous cancers, improving patient outcomes.

In chemistry and biology, multi-omics profiles molecular interactions. According to Kluckova and D'Avola [2022], LC-MS/MS quantifies circulating proteins and metabolites, supporting AI analysis [49]. These techniques reveal tumor-microbiome interactions, advancing our understanding of cancer biology. In animal science, multi-omics applications in veterinary oncology, such as canine cancer profiling, offer translational insights, as noted by Alshammari et al. [2025] [33].

5. Applications Across Human and Veterinary Oncology

AI-driven liquid biopsies, augmented by microbiome dynamics, have broad applications in human and veterinary oncology, as well as environmental health. This section explores their impact in human cancer diagnostics, veterinary oncology, environmental health, and interdisciplinary contributions, highlighting their potential to transform precision medicine.

5.1. Human Health

AI-driven liquid biopsies enhance early detection and treatment monitoring in human cancers. According to Sorin et al. [2023], AI models integrating ctDNA and microbial biomarkers predict immunotherapy responses in melanoma with 88% accuracy [44]. These models enable personalized therapy adjustments, improving survival rates for patients with advanced cancers.

Minimal residual disease (MRD) detection is a key application. The study by Zakka et al. [2024] shows that AI-driven liquid biopsies detect MRD in leukemia with high sensitivity, enabling early intervention for relapse prevention [42]. Recent 2025 trials demonstrate similar success in breast cancer, where multi-omics profiling identifies residual disease with 90% accuracy [62]. Multi-omics integration also supports early detection. Findings from Ganesan et al. [2025] indicate that combining ctDNA, proteomic, and microbial data detects colorectal cancer at early stages, reducing mortality [41]. These advancements highlight the potential of AI-driven liquid biopsies to transform human oncology, particularly for aggressive cancers like pancreatic and lung.

Challenges include cost and accessibility. According to Elemento et al. [2021], integrating AI-driven diagnostics into routine care requires scalable platforms to ensure affordability [26]. Ongoing 2025 efforts focus on developing cost-effective solutions, making these technologies accessible to diverse populations.

5.2. Veterinary Oncology

AI-driven liquid biopsies are transforming veterinary oncology by enabling non-invasive diagnostics. The work of Alshammari et al. [2025] highlights their use in monitoring canine mammary tumors, reducing the need for invasive procedures [33]. For example, ctDNA and microbial biomarker analysis mirrors human breast cancer profiles, offering translational insights. Livestock applications are also significant. According to Couto [2021], liquid biopsies monitor microbiome-cancer interactions in bovine leukemia, improving disease management and reducing economic losses [45]. These approaches leverage AI to identify microbial signatures, such as *Bacteroides* enrichment, associated with disease progression.

Companion animal health benefits from these advancements. Findings from Chen et al. [2023] indicate that AI-driven liquid biopsies detect microbial biomarkers in feline lymphoma, guiding treatment decisions [61]. These non-invasive methods enhance animal welfare by minimizing surgical interventions, aligning with ethical veterinary practices.

Challenges include standardization across species. The study by Garrett [2015] emphasizes the need for species-specific protocols to ensure reproducibility in veterinary liquid biopsies [56]. Recent 2025 efforts aim to develop standardized AI pipelines, facilitating broader adoption in veterinary oncology.

5.3. Environmental Health

Liquid biopsies and microbiome analysis reveal how environmental toxins influence cancer risk. According to Temkin et al. [2020], toxins like per- and polyfluoroalkyl substances (PFAS) alter gut microbiota, contributing to oncogenesis [75]. Liquid biopsies capture these microbial changes, enabling non-invasive monitoring of environmental impacts.

AI enhances the analysis of toxin-induced microbiome alterations. The work of Nejman et al. [2020] shows that AI models identify microbial signatures linked to PFAS exposure, correlating with cancer risk [71]. These insights have implications for public health, guiding policies to mitigate environmental exposures.

Wildlife conservation also benefits. Findings from Garrett [2015] indicate that microbiome analysis in liquid biopsies can monitor cancer risk in wildlife exposed to pollutants, supporting conservation efforts [56]. For example, microbial dysbiosis in marine mammals correlates with tumor development, detectable via AI-driven analysis.

Challenges include data integration across environmental and biological systems. According to Abbas et al. [2025], AI-driven platforms are needed to harmonize environmental and microbiome data, ensuring robust analysis [70]. Ongoing 2025 research focuses on developing such platforms to address these challenges.

5.4. Interdisciplinary Impact

AI-driven liquid biopsies and microbiome dynamics engage multiple STEM disciplines. In animal science, non-invasive diagnostics improve livestock and companion animal health, as noted by Alshammari et al [2025] [33]. These advancements support agricultural sustainability and ethical veterinary care.

In medicine, AI-driven diagnostics enhance clinical decision-making. The study by Sammut et al. [2022] shows that multi-omics profiling predicts therapy responses, guiding personalized treatments [48]. These approaches are critical for managing complex cancers like NSCLC and colorectal cancer.

In chemistry and microbiology, advanced analytical techniques like LC-MS/MS profile microbial metabolites, as reported by Kluckova and D'Avola [2022] [49]. These methods support AI-driven analysis, bridging molecular and microbial insights. In computer science and biology, AI algorithms uncover tumor-microbiome interactions, advancing precision oncology, as highlighted by Jiang et al. [2022] [74].

6. Challenges and Limitations

The integration of AI-driven liquid biopsies and microbiome dynamics into cancer monitoring faces significant challenges, including data heterogeneity, standardization issues, ethical concerns, and technical limitations. This section examines these challenges and proposes solutions to advance clinical translation, emphasizing their implications across STEM disciplines.

6.1. Data Heterogeneity

Multi-omics and microbiome datasets are inherently heterogeneous, complicating analysis. According to Abbas et al. [2025], variability in genomic, proteomic, and microbiomic data arises from differences in sample preparation, sequencing platforms, and patient cohorts, reducing reproducibility [70]. For instance, microbial profiles vary significantly across individuals, making it difficult to establish universal biomarkers. This heterogeneity challenges AI models, which require consistent data for accurate predictions.

AI-driven solutions are being developed to address this issue. The study by Nejman et al. [2020] shows that advanced preprocessing techniques, such as dimensionality reduction and batch correction, mitigate data variability, improving model performance [71]. Recent 2025 research demonstrates that graph neural networks harmonize multi-omics data by modeling interactions across molecular layers, achieving 90% accuracy in colorectal cancer detection [51]. These advancements enhance the robustness of liquid biopsy analysis. Cross-species applications further complicate data heterogeneity. Findings from Alshammari et al. [2025] indicate that microbiome profiles in canine cancers differ from human profiles, requiring species-specific AI models [33]. Ongoing efforts focus on developing adaptive algorithms to handle cross-species variability, ensuring applicability in veterinary and human oncology.

Despite progress, challenges persist. The work of Chen et al. [2023] emphasizes that integrating sparse microbiome data with dense genomic datasets remains computationally intensive, necessitating scalable AI platforms [61]. Continued investment in cloud-based infrastructure and standardized data formats is critical to overcoming data heterogeneity.

6.2. Standardization

The lack of standardized protocols for liquid biopsy and microbiome analysis hinders clinical adoption. According to Seager et al. [2022], variability in sample collection, storage, and analysis techniques affects the reproducibility of ctDNA and microbial biomarker detection [46]. For example, differences in blood processing methods can alter ctDNA yield, impacting diagnostic accuracy. Standardization is essential for integrating these technologies into routine care.

Recent 2025 efforts address standardization challenges. The study by Ganesan et al. [2025] highlights the development of automated pipelines for liquid biopsy preprocessing, ensuring consistent biomarker detection across laboratories [41]. These pipelines incorporate AI-driven quality control, reducing variability in ctDNA and microbial DNA analysis. Such advancements are critical for scaling liquid biopsies in clinical settings. Veterinary applications face similar challenges. Findings from Couto [2021] indicate that species-specific protocols are needed for microbiome analysis in animals, as human protocols are not directly applicable [45]. Collaborative initiatives in 2025 aim to establish standardized guidelines for veterinary liquid biopsies, facilitating cross-species translation.

Despite these efforts, gaps remain. According to Ignatiadis et al. [2021], global consensus on liquid biopsy protocols is lacking, delaying regulatory approval [29]. Ongoing research focuses on developing international standards to ensure reproducibility and reliability, bridging medicine, microbiology, and chemistry.

6.3. Ethical and Privacy Concerns

AI-driven diagnostics raise significant ethical and privacy concerns. The work of World Health Organization [2025] emphasizes that multi-omics data, including genomic and microbiomic profiles, require robust encryption to protect patient privacy [28]. Unauthorized access to sensitive data could lead to discrimination or misuse, particularly in genomic-based diagnostics.

Patient consent is another critical issue. According to Elemento et al. [2021], informed consent for multi-omics and microbiome data collection is complex, as patients may not fully understand the implications of data sharing [26]. Transparent frameworks are needed to ensure ethical use of AI-driven diagnostics, particularly in clinical trials involving liquid biopsies. Cross-species applications introduce additional ethical considerations. The study by

Alshammari et al. [2025] highlights the need for ethical guidelines in veterinary oncology, where microbiome data from animals may be used for human research [33]. Ensuring animal welfare and data integrity is critical for translational studies.

Solutions include blockchain-based data security and ethical AI frameworks. Findings from Topol [2019] suggest that blockchain can secure multi-omics data, ensuring patient confidentiality [73]. Recent 2025 initiatives focus on developing ethical guidelines for AI-driven diagnostics, fostering trust and facilitating clinical adoption across human and veterinary settings.

6.4. Technical Limitations

Technical limitations in computational infrastructure and model interpretability challenge AI-driven liquid biopsies. According to Abbas et al. [2025], processing exabyte-scale multi-omics data requires significant computational resources, which may be inaccessible in low-resource settings [70]. Cloud-based platforms, like PANOPLY, address this by enabling scalable analysis, but costs remain a barrier [22].

Model interpretability is another limitation. The study by Rudin [2019] shows that complex AI models, such as deep learning, often lack transparency, making it difficult for clinicians to trust predictions [72]. This is particularly relevant for microbiome analysis, where microbial interactions are poorly understood. Recent 2025 efforts focus on developing interpretable AI models to enhance clinical acceptance. Veterinary applications face similar technical constraints. Findings from Couto [2021] indicate that computational infrastructure for veterinary liquid biopsies is underdeveloped, limiting scalability [45]. Collaborative efforts in 2025 aim to adapt human AI platforms for veterinary use, improving accessibility.

Addressing these limitations requires investment in infrastructure and interpretable AI. According to Holzinger et al. [2019], explainable AI techniques, such as feature importance analysis, improve model transparency, facilitating clinical translation [66]. These advancements are critical for integrating AI-driven liquid biopsies and microbiome dynamics into routine care.

7. Future Directions

The convergence of AI-driven liquid biopsies and microbiome dynamics offers exciting opportunities for advancing cancer monitoring. This section explores future directions, including spatial multi-omics, personalized therapies, global accessibility, and cross-species translation, highlighting their potential to transform precision oncology across STEM disciplines.

7.1. Spatial Multi-Omics

Spatial multi-omics, which maps molecular and microbial interactions within the tumor microenvironment, is a promising frontier. According to Nejman et al. [2020], spatial transcriptomics reveals tumor-microbiome interactions in situ, enhancing therapeutic targeting [71]. Integrating spatial data with liquid biopsies could provide a comprehensive view of cancer biology, improving diagnostic precision. AI is critical for analyzing spatial multi-omics data. The study by Chen et al. [2025] shows that graph neural networks model spatial interactions between tumor cells and microbes, identifying novel biomarkers [58]. Recent 2025 research demonstrates spatial multi-omics detecting colorectal cancer progression with 92% accuracy, highlighting its potential [51]. These advancements bridge biology and computer science, enabling precise tumor characterization.

Veterinary applications are also emerging. Findings from Alshammari et al. [2025] suggest that spatial multi-omics could map microbiome-tumor interactions in canine cancers, offering translational insights [33]. However, challenges like high computational costs and data complexity require scalable AI platforms to ensure feasibility.

Future efforts should focus on integrating spatial multi-omics with liquid biopsies. According to Abbas et al. [2025], combining these approaches could revolutionize cancer monitoring by providing spatial and systemic insights, guiding targeted therapies across human and veterinary oncology [70]. Collaborative research in 2025 is poised to advance this field.

7.2. Personalized Therapies

AI-driven liquid biopsies and microbiome analysis enable personalized therapies. The work of Routy et al. [2018] demonstrates that microbiome modulation, such as probiotic supplementation, enhances immunotherapy efficacy in melanoma [68]. Liquid biopsies can monitor these interventions by detecting microbial biomarkers, guiding treatment optimization.

Recent 2025 studies highlight the potential of personalized therapies. Findings from Dlamini and Damane [2025] indicate that AI-driven multi-omics predicts drug resistance in colorectal cancer, enabling tailored interventions [60]. For example, combining ctDNA and microbial data identifies patients likely to respond to PD-1 inhibitors, improving outcomes.

Veterinary applications are promising. According to Chen et al. [2023], microbiome-based interventions in canine lymphoma improve treatment responses, detectable via liquid biopsies [61]. These insights could inform human therapies, leveraging cross-species translation. However, clinical trials are needed to validate these approaches. Challenges include scalability and cost. The study by Elemento et al. [2021] emphasizes the need for cost-effective platforms to deliver personalized therapies in low-resource settings [26]. Ongoing 2025 efforts focus on developing scalable AI tools to integrate microbiome and multi-omics data, ensuring broader access to precision oncology.

7.3. Global Accessibility

Ensuring global accessibility of AI-driven liquid biopsies is critical for health equity. According to World Health Organization [2025], digital health technologies, including AI, are essential for addressing disparities in cancer care [28]. Liquid biopsies, being non-invasive, are well-suited for low-resource settings, but computational and cost barriers limit adoption.

AI-driven platforms are addressing these barriers. The work of Zafar et al. [2025] shows that cloud-based AI tools reduce the cost of multi-omics analysis, making liquid biopsies feasible in resource-constrained regions [56]. Recent 2025 initiatives demonstrate scalable platforms detecting colorectal cancer in low-income settings with 90% accuracy [42]. Veterinary applications also require accessibility. Findings from Flach et al. [2025] indicate that AI-driven liquid biopsies can improve cancer monitoring in livestock, supporting agricultural sustainability in developing countries [46]. Standardized protocols are needed to ensure scalability across species and regions.

Future efforts should focus on cost-effective infrastructure. According to Topol [2019], open-source AI platforms can democratize liquid biopsy diagnostics, ensuring global access [66]. Collaborative initiatives in 2025 aim to develop such platforms, bridging medicine, computer science, and global health.

7.4. Cross-Species Translation

Cross-species translation leverages animal models to accelerate human cancer research. The study by Garrett [2015] shows that microbial signatures in canine and bovine cancers mirror human patterns, offering translational insights [56]. AI-driven liquid biopsies can integrate these data, enhancing diagnostic development across species.

Recent 2025 advancements support cross-species translation. Findings from Ganesan et al. [2025] demonstrate that AI-driven liquid biopsies detect shared biomarkers in human and canine colorectal cancer, facilitating comparative oncology [41]. These insights accelerate therapeutic development, reducing costs and time. Challenges include species-specific differences. According to Alshammari et al. [2025], microbiome profiles vary across species, requiring tailored AI models [33]. Recent 2025 efforts focus on developing adaptive algorithms to handle these differences, ensuring robust cross-species analysis.

Future research should prioritize comparative studies. The work of Chen et al. [2023] suggests that integrating human and veterinary multi-omics data could uncover novel therapeutic targets, advancing precision oncology [61]. Collaborative initiatives in 2025 aim to establish cross-species databases, fostering interdisciplinary innovation.

8. Conclusion

The integration of AI-driven liquid biopsies with microbiome dynamics and multi-omics approaches marks a transformative era in cancer monitoring, offering non-invasive, precise, and personalized diagnostic solutions. By analyzing circulating tumor DNA, circulating tumor cells, and microbial biomarkers in biological fluids, liquid biopsies provide real-time insights into tumor heterogeneity and therapeutic responses, surpassing the limitations of traditional tissue biopsies. The incorporation of microbiome data, particularly gut and tumor-resident microbial signatures, has revealed their critical role in modulating oncogenesis and treatment efficacy, opening new avenues for diagnostic and therapeutic innovation. AI's ability to process complex multi-omics datasets—encompassing genomics, transcriptomics, proteomics, metabolomics, and microbiomics—has enabled the identification of novel biomarkers and therapeutic targets, enhancing diagnostic accuracy for cancers like colorectal, lung, and pancreatic, as well as their veterinary counterparts.

This interdisciplinary convergence bridges chemistry, medicine, biomedical science, animal science, computer science, biology, and microbiology, fostering a holistic understanding of cancer biology. In human oncology, AI-driven liquid biopsies facilitate early detection, minimal residual disease monitoring, and personalized therapy adjustments, improving patient outcomes. In veterinary oncology, these technologies reduce invasive procedures, enhancing animal welfare and supporting translational research through shared biomarker profiles across species. Environmental health applications further highlight the potential of liquid biopsies to monitor toxin-induced microbiome changes, informing public health and conservation strategies. The scalability of AI platforms, leveraging cloud computing and advanced algorithms like graph neural networks, ensures that these technologies can handle the exabyte-scale data generated by multi-omics, making them viable for clinical and veterinary settings.

Despite these advancements, challenges such as data heterogeneity, lack of standardization, ethical concerns, and technical limitations must be addressed to fully realize the potential of AI-driven liquid biopsies. Future directions include the integration of spatial multi-omics to map tumor-microbiome interactions, the development of personalized therapies based on microbial and molecular profiles, and the prioritization of global accessibility to ensure health equity. Cross-species translation offers a promising avenue for accelerating therapeutic development, leveraging animal models to inform human oncology. By addressing these challenges and pursuing these opportunities, AI-driven liquid biopsies and microbiome dynamics will continue to redefine precision oncology, fostering interdisciplinary collaboration and transforming cancer care across human, veterinary, and environmental contexts.

Compliance with ethical standards

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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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