

The future of early cancer detection: emerging diagnostic technologies for liver and ovarian cancers

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Abstract

Background

Liver and ovarian cancers are often diagnosed at advanced stages due to the absence of, or vague, early-stage symptoms. Current diagnostic approaches have limitations in accuracy, accessibility, and scalability, highlighting the need for innovative methods to support earlier detection. This study employed horizon scanning and evidence synthesis methods to identify emerging technologies for early detection of liver and ovarian cancers.

Methods

Clinical trial registries and academic databases were searched for studies published from January 2022 to October 2025. Eligible technologies for early detection or triage were estimated to be within 0–7 years of potential market access and suitable for use outside secondary care settings. Identified technologies were then mapped based on indication, test type, sample type, and technology readiness level (TRL).

Results

Sixty-one liver cancer technologies were identified from the literature, comprising 45 biomarker tests, five artificial intelligence (AI) and digital tests, and 11 tests integrating biomarkers and multimodal approaches. For ovarian cancer, 41 technologies were identified from the literature, comprising 24 biomarkers tests, 12 AI and digital tests, and five biomarker-integrated or multimodal approaches. Most technologies were at an early stage of development (TRL < 6), with blood-based samples (blood, serum, plasma) dominating across both cancers. In addition, 13 clinical trial records were identified including 10 for liver cancer and three for ovarian cancer.

Conclusions

A rapidly evolving pipeline of technologies for early detection of liver and ovarian cancers is emerging. Current development trends favour multimodal approaches that combine multiple biomarkers, or multiple modalities (e.g. combination of biomarkers and AI). The predominance of blood-based testing among identified technologies highlights the potential for implementation beyond secondary-care settings. However, robust clinical validation and investment in infrastructure, standardisation, and equitable implementation will be required before widespread adoption.

Background

Ovarian and liver cancers account for substantial cancer-related mortality, largely due to diagnosis at advanced stages when curative treatment options are limited.^{1–3} Late diagnosis is driven in part by non-specific or absent early symptoms and the limitations of current early detection methods.^{4–6} Liver cancer is often called a “silent killer” due to the absence of early symptoms, leading to delayed diagnosis.⁷ Despite advances in surveillance and treatment, liver cancer remains a leading cause of cancer-related death worldwide and, survival outcomes remain poor.^{6, 8} Early diagnosis substantially improves outcomes,^{6, 9, 10}

however, detection rates remain low, largely due to delays in diagnostic pathways, inadequate risk recognition, inconsistent monitoring, and limitations in imaging visibility.^{6, 11}

Regular surveillance for liver cancer (hepatocellular carcinoma), typically at six-month intervals, is recommended for individuals at high-risk and can improve the likelihood of early detection; however, national screening programmes remain absent in many countries.^{3, 12} Current surveillance strategies rely on alpha-fetoprotein (AFP) testing and imaging modalities, such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). However, their effectiveness is constrained by the non-specific nature of symptoms and the limited diagnostic performance of existing tests.^{3, 13, 14} While MRI offers greater sensitivity, its use is limited by cost and accessibility,¹⁵ and the overall performance of existing surveillance approaches remains suboptimal. Additional barriers include limited awareness, restricted access, logistical constraints, sociocultural influences, and delays in service delivery.^{16–18}

Ovarian cancer is a growing global health burden that is often diagnosed late, with only 38% of cases in England detected at stages I–II.¹⁹ Consequently, five-year survival declines from approximately 95% for stage I disease to 15% for stage IV disease.²⁰ Although routine screening for ovarian cancer is not currently recommended, emerging research initiatives, such as the EU-funded DISARM project, are investigating approaches to improve personalised risk assessment and develop new strategies for earlier detection.^{21–23} Early detection remains challenging because of limitations in understanding tumour biology, identifying high-risk groups, and determining reliable biomarkers, alongside barriers to accessing diagnostic services (predominantly delivered in clinical settings).^{24–26} Current diagnostic approaches, including CA125 (a blood protein used as a tumour marker) and transvaginal ultrasound, have recognised limitations in accuracy and practicality.^{4, 27–29} CA125 is often elevated only in advanced disease and varies by tumour histological subtype, contributing to delayed diagnosis.^{26, 30, 31}

These limitations highlight a clear unmet need for novel diagnostic approaches that offer improved accuracy, scalability, and accessibility to enable earlier detection of liver cancer and ovarian cancer.^{32–36} Expanding diagnostic capacity beyond secondary care could reduce diagnostic delays, improve access to testing, and support earlier diagnosis. Understanding emerging technologies is therefore critical for informing future service planning and implementation, particularly where innovations have the potential to streamline diagnostic pathways and promote equitable access to care. In response to these challenges, a horizon scan and evidence synthesis were undertaken to identify emerging technologies for the early detection of liver and ovarian cancers. This paper aims to describe technologies in development with potential use outside secondary care and to characterise the diagnostic modalities underpinning these approaches.

Methods

Scope and eligibility criteria

Methods for this study were prespecified in a protocol published on the Open Science Framework.³⁷ The findings presented here focus on liver cancer and ovarian cancer, with the generic cancer component described elsewhere.³⁸ Evidence synthesis methods were combined with horizon scanning, drawing on data from trial registries and academic literature. Technologies in early clinical or pre-regulatory development were

identified using predefined inclusion criteria based on the population, intervention, comparator, outcomes, and setting (PICOS) framework:

- **Population:** Any (children and adults)
- **Intervention:** Technologies in development for triaging patients with suspected liver cancer and/or ovarian cancer. These included bio-marker-based tests (e.g. blood, urine, smear, stool or saliva), artificial intelligence (AI) and digital technologies, and multimodal approaches combining biomarkers with algorithms, imaging and other data sources.
- **Comparator:** Any comparator, including standard care or no comparator.
- **Outcomes:** Overview of the technology, including diagnostic accuracy if available.
- **Setting:** Tests with potential for use outside secondary care settings (e.g., primary care, community diagnostic centres, or home-base environments). Technologies were required to be non-invasive or minimally invasive, not requiring hospital-level monitoring, and be feasible without specialised equipment or personnel for sample collection. Analysis and interpretation could be performed by specialist staff.

Search strategy

A MEDLINE (Ovid) search strategy was developed and peer-reviewed, with additional searches in ClinicalTrials.gov and the World Health Organization (WHO) International Clinical Trials Registries Platform (ICTRP). Searches were limited to studies published between 1st January 2022 and 13th October 2025 to focus on emerging technologies in translational development. Searches were restricted to English-language publications, and reference lists of relevant systematic reviews were screened to identify additional studies (Supplementary Material 1).

Screening

Search results were deduplicated and screened in Rayyan.³⁹ Titles and abstracts were screened against the inclusion criteria following an initial calibration exercise, during which 100 studies were reviewed by six reviewers. A subset of records (n = 600) was independently screened in duplicate to assess consistency in study selection. Full texts of potentially eligible studies were retrieved and screened in Covidence.⁴⁰ Disagreements were resolved through discussion or, where necessary adjudication by a third-reviewer. Following establishment of reviewer agreement, single screening was resumed with ongoing quality checks at both title/abstract and full text stages. As clinical setting was rarely reported, sample type (e.g., blood, saliva, urine) was used as a proxy indicator of potential applicability in primary care or community settings.

Data extraction

The data extraction form captured study characteristics, population, technologies, diagnostic accuracy, implementation data, clinical trial information, and technology readiness levels (TRLs). TRLs were used to assess the maturity of each technology, ranging from early-stage concept development and laboratory validation to technologies that have been evaluated in real-world settings and are approaching implementation.^{41, 42} Technologies were assigned a TRL based on the stage of development and validation reported in the available evidence. Data were recorded in a structured Excel sheet. Data extraction was piloted among multiple reviewers to ensure consistency before being conducted independently by single reviewers.

Quality assurance included post-extraction spot checks and independent double-checking of a random 10% sample, with discrepancies resolved by consensus.

Data analysis

Technologies were the unit of analysis. Where multiple studies assessed the same technology, the most recent study was used as the primary reference, with earlier studies retained as supplementary sources. Clinical trial records were reported and analysed separately from studies retrieved from the literature due to difficulties ascertaining unique technologies. Where possible, trial records were matched to corresponding published studies, and trial registration identifiers were recorded.

Technologies integrating biomarkers with complementary modalities (e.g., AI, biospectroscopy, or nanoflow cytometry) or employing alternative approaches (e.g. imaging-based technologies) were categorised as 'other'. Biomarker studies were classified by biomarker type using the classification system reported in Ahmad et al.⁴³ while the accompanying modalities were categorised as reported in the original studies.

Results

Identified studies

Following deduplication, 5,293 records were identified: 4,791 from Ovid (MEDLINE) and 502 from clinical trial registries (Fig. 1). The review included 102 technologies (61 liver cancer; 41 ovarian cancer) and 13 clinical trial registry records (10 liver cancer, and three ovarian cancer (Supplementary Material 2).

Technology characteristics

Liver cancer

Overall, 10 clinical trial records were included. All evaluated blood-based biomarker tests for early liver cancer detection, except one study investigating an AI-enabled electrocardiogram. Two trial records were matched to studies retrieved from the literature and were analysed as part of the technologies reported in the literature search. In total, 61 technologies for liver cancer detection were identified from the literature including 45 biomarker technologies, five AI and digital technologies, and 11 classified as "other". Most technologies (n = 48) were at TRL-4 (Fig. 2). The most frequently recorded sample types were blood (n = 32), plasma (n = 16) and serum (n = 5) (Fig. 3).

Biomarkers

Biomarker-based technologies were the largest group (n = 45) and were predominantly at an early stage of development, with most classified as TRL-4 (n = 38). Only one, proteomic, biomarker had reached TRL-8.⁴⁵ Most technologies (78%) used multi-marker panels, and 89% analysed blood-based samples (blood, plasma, or serum). Only two technologies used urine (circRNA biomarkers⁴⁶ and neutrophil gelatinase-associated lipocalin⁴⁷), and one used saliva (differentially expressed miRNAs).⁴⁸ Biomarker categories included proteomic

(n = 13), multi-type (n = 9), transcriptomic (n = 9), and epigenetic (n = 8), genetic (n = 4), lipidomic (n = 1), and metabolomic (n = 1) technologies (Table 1 and Supplementary Material 3, Figure S1).

Emerging AI and digital technologies

Only five AI and digital technologies were identified, all at an early stage of development (TRL-3 or TRL-4). These technologies used machine learning or statistical models to analyse clinical and biological data for disease detection, screening, and prediction, with most (80%) using blood-based samples (Table 1 and Supplementary Material 3, Figure S1). One machine learning approach used patient demographic, clinical, healthcare, and prior screening data to predict hepatocellular carcinoma surveillance completion, supporting more targeted and cost-effective surveillance strategies.⁴⁹

Other technologies

Eleven technologies combined biomarkers with AI or other approaches. Most were in the early stages of development (TRL-3 or TRL-4), although three had reached TRL-6 or TRL-7.^{50–52} All used blood-based samples. Three combined biomarkers with spectroscopy, while the remaining eight combined biomarkers with AI or machine learning (Table 1 and Supplementary Material 3, Figure S1).

Table 1
Summary of characteristics of biomarker, AI/digital, and other emerging technologies for liver cancer detection

Characteristic	Biomarker technologies (n = 45)	AI & digital technologies (n = 5)	Other technologies (n = 11)
Most common TRL	TRL-4 (n = 38)	TRL-3 to TRL-4	TRL-4
Highest TRL	TRL-8 (n = 1)	TRL-4	TRL-7
Main sample type	Blood (89%)	Blood (80%)	Blood (100%)
Alternative sample types	Urine (n = 2), saliva (n = 1)	Patient data (n = 1)	None
Dominant approach	Multi-marker panels (78%)	Machine learning/statistical modelling	Biomarkers + AI (n = 8) Biomarkers + spectroscopy (n = 3)
Most common biomarker categories	Proteomic, multi-type, transcriptomic, epigenetic	Not relevant	Epigenetic, proteomic, metabolomic, multi-type
AI = Artificial intelligence; TRL = Technology readiness level			

Technologies ≥ TRL-6

Only four liver cancer technologies had reached TRL-6 or higher.^{45, 50–52} These more advanced technologies were examined to assess implementation requirements, including the need for specialist personnel and

potential demands on the healthcare system. All required blood-derived samples, and no cost-effectiveness evidence was identified for any technology. (Table 2).

Table 2
Subset of technologies for liver cancer detection that have TRL-6 and above

Name of test	Description of test	Sample type	Setting	Operator	Cost effectiveness	Technology Readiness Level (TRLs)
GALAD score ⁴⁵	AFP, AFP-L3%, PIVKA-II	Serum	Hospital clinical laboratories - Given the sample type, test could be used in GP setting/outside of secondary care	Healthcare professional - Given the sample type this is not suitable for self-administration	Not reported	TRL-8
Doylestown Plus and GALAD Score ⁵²	Doylestown Plus and GALAD score	Plasma and serum	Clinic - Given the sample type, test could be used in GP setting/outside of secondary care	Not reported - Given the sample type this is not suitable for self-administration	Not reported	TRL-7
Not reported ⁵¹	Male-ABCD algorithm	Blood	Clinic - Given the sample type, test could be used in GP setting/outside of secondary care	Healthcare professional - Given the sample type this is not suitable for self-administration	Not reported	TRL-7
HelioLiver ⁵⁰	cfDNA methylation markers 77 CpG sites across 28 genes, AFP, AFP-L3%, DCP	Plasma	Hospital - Given the sample type, test could be used in GP setting/outside of secondary care	Healthcare professional - Given the sample type this is not suitable for self-administration	Not reported	TRL-6
AFP = Alpha-Fetoprotein; AFP-L3 = Alpha-Fetoprotein-L3; cfDNA = cell-free DNA; DCP = Des-gamma-carboxyprothrombin; GALAD = Gender, Age, Alpha-Fetoprotein-L3, Alpha-Fetoprotein, and Des-carboxy-prothrombin; GP = General Practitioner; PIVKA-II = Protein Induced by Vitamin K Absence or Antagonist-II						

Ovarian Cancer

Overall, three clinical trial records were retrieved. All evaluated biomarker tests, two of which used blood-based samples, and one did not report the sample type. One trial record corresponded to a study retrieved in the literature and was analysed as part of the literature-derived technologies. In total, 41 technologies for ovarian cancer detection were identified from the literature including 24 biomarker technologies, 12 AI and digital

technologies, and five classified as “other”. Most technologies (88%) were at TRL-4 (Fig. 2). Most common types of samples used were blood (n = 19), serum (n = 7), and plasma (n = 6) (Fig. 4).

Biomarkers

Biomarker-based technologies represented the largest group of emerging ovarian cancer detection approaches and were predominantly at TRL-4 (83%), with one technology at TRL-3 and three at TRL-5. Most focused on multi-marker panels (67%) and used blood-based samples (92%). Alternative sampling approaches included urine-derived miRNA biomarkers,⁵³ cervico-vaginal fluid collected using a Pap smear-like method,⁵⁴ and non-invasive assessment of CXCL13 mRNA using imaging and transcriptomic sequencing.⁵⁵ Technologies spanned multiple biomarker categories, including proteomic (n = 7), transcriptomic (n = 5), multi-type (n = 5), epigenetic (n = 4), genetic (n = 1), lipidomic (n = 1), metabolomic (n = 1) (Table 3 and Supplementary Material 3, Figure S2).

AI and digital technologies

AI and digital technologies included 12 TRL-4 technologies for early ovarian cancer detection. Most used machine learning algorithms, including Random Forest and Support Vector Machine,⁵⁶ while one applied deep learning.⁵⁷ Approximately two-thirds incorporated blood-based biomarkers (e.g., CA125 and HE4), whereas others analysed DNA methylation^{56, 57} or metabolomic signatures.⁵⁸ Four technologies used patient clinical data, with some incorporating laboratory test results,^{56, 57, 59, 60} and one combined machine learning with mass spectrometry⁶¹ (Table 3 and Supplementary Material 3, Figure S2).

Other technologies

Five technologies combined biomarkers with complementary modalities, including AI, biospectroscopy, and nanoflow cytometry, while one employed an imaging-based approach. Four were classified as TRL-4^{62–65} and one imaging-based technology as TRL-5.⁶⁶ Most used blood-based samples, except the imaging-only approach.⁶⁶ Applications included transcriptomic biomarkers with machine learning,⁶⁴ genetic biomarkers with risk prediction model,⁶⁵ proteomic biomarkers with biospectroscopy,⁶³ and proteomic profiling using nanoflow cytometry⁶² (Table 3 and Supplementary Material 3, Figure S2).

Table 3

Summary of characteristics of biomarker, AI/digital, and other emerging technologies for ovarian cancer detection

Characteristic	Biomarker technologies (n = 24)	AI & digital technologies (n = 12)	Other technologies (n = 5)
Most common TRL	TRL-4 (n = 20)	TRL-4 (n = 12)	TRL-4 (n = 4)
Highest TRL	TRL-5 (n = 3)	TRL-4	TRL-5 (n = 1)
Main sample type	Blood (n = 22)	Blood-based biomarkers and patient clinical data	Blood (n = 4)
Alternative sample types	Urine-derived miRNA; cervico-vaginal fluid; imaging-derived CXCL13 mRNA assessment.	Blood and urine	Imaging-only technology
Dominant approach	Multi-marker biomarker panels (67%)	Machine learning (Random Forest, SVM); one deep learning model.	Biomarkers integrated with AI, biospectroscopy, imaging, or nanoflow cytometry.
Most common biomarker categories	Proteomic (n = 7), transcriptomic (n = 5), multi-type (n = 5), epigenetic (n = 4)	Not relevant	Proteomic, genetic, and transcriptomic biomarkers
AI = Artificial intelligence; CXCL13 = C-X-C motif chemokine ligand 13; miRNA= Micro ribonucleic acid; mRNA = Messenger ribonucleic acid; TRL = Technology readiness level			

Discussion

This horizon scan and evidence synthesis identified 102 technologies for the early detection of liver and ovarian cancers that have potential for use outside secondary-care settings (n = 61 for liver cancer and n = 41 for ovarian cancer). Most technologies were biomarker-based (n = 69), and at an early stage of development. However, a substantial proportion incorporated AI and digital tools, or other complementary modalities, highlighting growing interest in more integrated approaches to cancer detection, and reflecting efforts to improve diagnostic performance beyond that achievable with individual biomarkers. This trend is consistent with a recent umbrella review showing that integrating multi-omics data (e.g., genomics, transcriptomics, epigenomics) with imaging modalities (e.g., MRI, CT, positron emission tomography) can enhance diagnostic, prognostic, and predictive accuracy compared with single-modality approaches.⁶⁷

Biomarkers already used in clinical practice, such as AFP for liver cancer⁶⁸ and CA125 for ovarian cancer, are increasingly incorporated into multi-marker panels alongside emerging biomarkers to enhance diagnostic performance.⁶⁹ This is supported by studies showing that AFP alone has limited sensitivity for liver cancer (approximately 40–65%),⁷⁰ while multi-marker panels incorporating PIVKA-II, AFP-L3 plus PIVKA-II, or Golgi-specific membrane protein (GP73) demonstrate improved sensitivity, exceeding 80% in reported studies.^{13, 14} Similarly, CA125 alone misses a considerable proportion of ovarian cancers (23%), whereas multi-marker panels such as the Ovarian Cancer Score (CA125, HE4, C5a) achieve higher performance (sensitivity 95.4%,

specificity 90.4%).⁷¹ Collectively, these findings highlight the growing interest in multi-marker approaches as a means of improving the diagnostic performance of early cancer detection technologies.^{67, 72, 73}

Blood-based samples were the predominant sample type across both biomarker-based and AI-enabled technologies identified in this scan.⁷⁴ This reflects the growing interest in liquid biopsy approaches, which offer a minimally invasive and potentially cost-effective method for cancer detection. However, broader implementation remains constrained by challenges including low biomarker abundance, variable diagnostic performance, pre-analytical variability in sample collection and processing, and the lack of standardised protocols and quality-control frameworks.^{74–76} In addition, the need for specialised equipment and analytical expertise may increase costs and limit scalability in routine clinical practice.⁷⁴ The predominance of blood-based testing also highlights opportunities for future use outside traditional healthcare settings, including home-based sample collection. While capillary blood sampling has shown promise in other cancers and chronic diseases,^{77–79} its application in oncology screening remains limited by concerns regarding sample quality, standardisation, and analytical reproducibility.^{74–76} Although further validation is needed, evidence from established self-sampling programmes indicates that home-based testing may improve screening uptake and support earlier diagnosis.^{80–82}

More broadly, most technologies in this scan remain at early-stage of development (TRL-4), with validation largely confined to laboratory settings and limited testing in clinical or real-world environments. Progression to higher readiness levels will require robust evaluation of safety, clinical effectiveness, and usability.^{41, 83} Given that the current evidence base is derived predominantly from observational and laboratory studies, there is a clear need for well-designed clinical validation studies, alongside the generation of real-world evidence to establish effectiveness and cost-effectiveness. Furthermore, many technologies have undergone limited external validation, highlighting the need for evaluation across diverse populations and healthcare settings, particularly for AI-enabled and multi-marker approaches. As diagnostic technologies become increasingly sensitive, consideration must also be given to the risk of false-positive findings and overdiagnosis. Although earlier detection may improve clinical outcomes, it may also identify lesions or abnormalities that would not progress to clinically significant disease, potentially resulting in unnecessary investigations, patient anxiety, and increased healthcare utilisation.^{84–86}

Strengths and limitations

This horizon scan and evidence synthesis is the first to systematically assess emerging technologies for the early detection of liver and ovarian cancers. Evidence was identified through searches of core bibliographic databases, clinical trial registries, and backward citation chaining. A pragmatic search strategy was used to manage the high volume of irrelevant cancer literature. Potential missed studies were mitigated through iterative piloting, refinement, and review with clinical experts and information specialists. Searches were limited to English-language studies published from 2022 onwards, supplemented by eligible studies identified through the wider project from 2020 onwards. Clinical trial records were assessed separately from published studies, as the uniqueness of registry-reported technologies could not be reliably established. Records were cross-checked against published studies to minimise duplication, although some overlap may remain.

The evidence base was limited by sparse reporting of cost-effectiveness data, and incomplete reporting of clinical setting, staffing, and resource requirements, restricting assessment of implementation readiness. Most identified technologies were at early stages of development, with limited robust evidence on performance. Additionally, the predominance of observational or non-clinical studies and substantial clinical heterogeneity constrained meaningful comparison across technologies.

Recommendations for research and policy

Emerging technologies such as biomarkers and AI-based tools show promise for extending cancer detection beyond hospitals, including in primary care, community, and home settings. Although many remain at an early stage of development, these innovations indicate a shift towards more integrated, multimodal diagnostic pathways. Future programmes could benefit from combining these approaches with home-based and non-invasive tests to improve accessibility and uptake. However, progress towards implementation will require investment in clinical validation, infrastructure, and standardisation to support accurate, scalable, and equitable adoption. Further research should focus on generating robust clinical and real-world evidence, evaluating cost-effectiveness and resource implications, and informing implementation strategies. Alongside this, the development of clear guidelines, quality standards, and regulatory frameworks for sample collection, AI integration, processing, and analysis will help improve consistency, ensure quality assurance, and support the reliable implementation.

Conclusions

The insights generated from this horizon scan and evidence synthesis can inform future health system planning by identifying technologies with the potential for adoption across primary care, community, and home settings. Emerging biomarker-based, AI-enabled, and other technologies indicate a shift towards more integrated, multimodal approaches to cancer detection beyond secondary care. However, further clinical and real-world evidence is needed to establish their accuracy, feasibility, cost-effectiveness, and potential role screening pathways. As these technologies mature, programmes may benefit from prioritising promising non-invasive technologies, including home-based innovations, alongside investment in validation, infrastructure, and standards to support equitable and reliable early cancer detection.

Declarations

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Declaration of conflicting interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

AI Declaration

An AI tool was used to support the creation of Table 1 and Table 3. The authors reviewed and verified the final tables.

Ethics Statement

Not applicable. This study did not require ethical board approval as it is a horizon scan and evidence synthesis and did not involve the primary collection of animal and patient data.

Data availability statement

All data used in this study were obtained from publicly available sources. The complete extracted dataset supporting the findings is provided in Supplementary Material 2.

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Figures

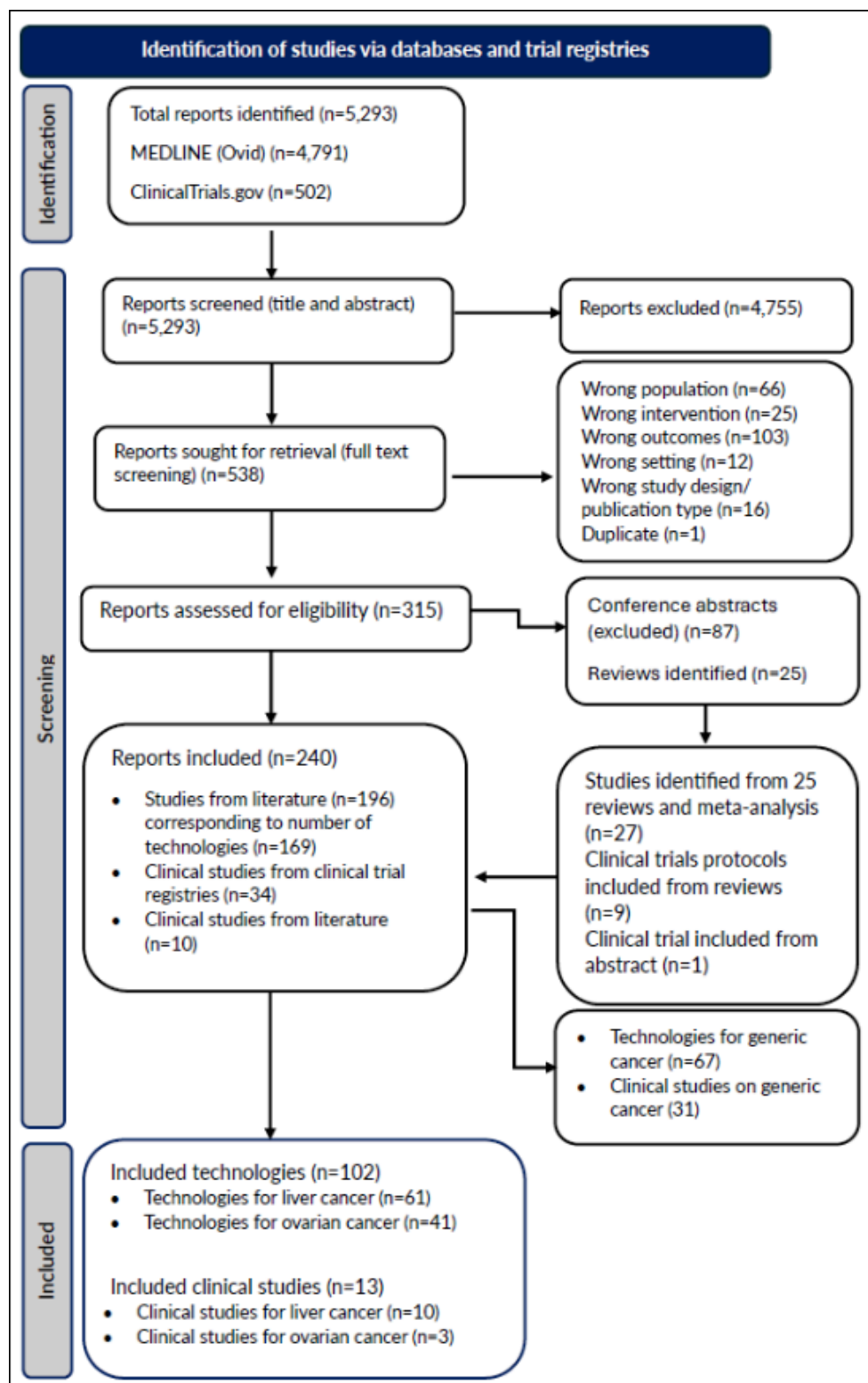


Figure 1

PRISMA flowchart for early cancer detection technologies. Adapted from: Page, et al. 2021.⁴⁴

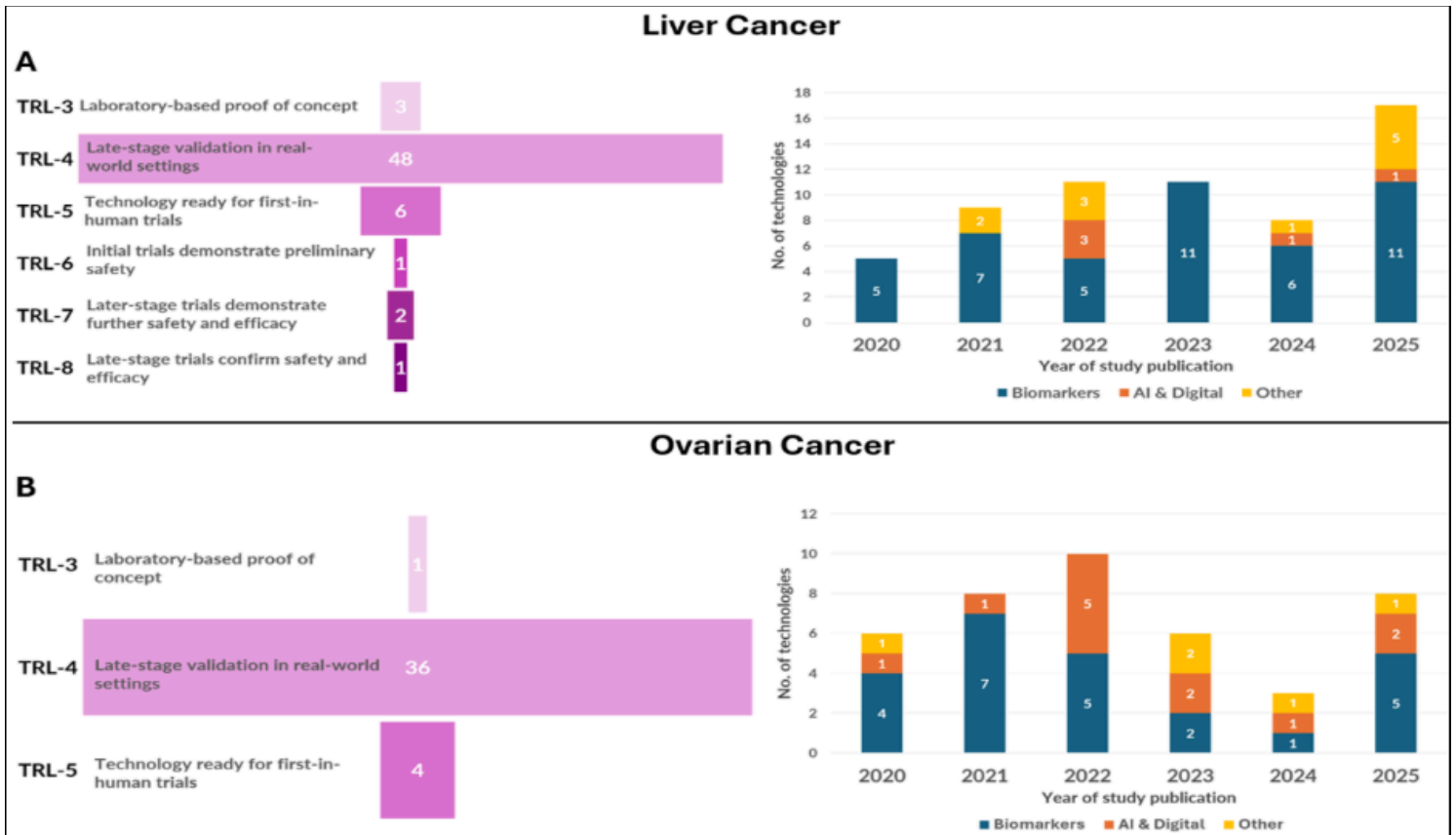


Figure 2

Technology Readiness Level (TRL) distribution of identified technologies and number of technologies by category and year of study publication for liver (A) and ovarian (B) cancer.

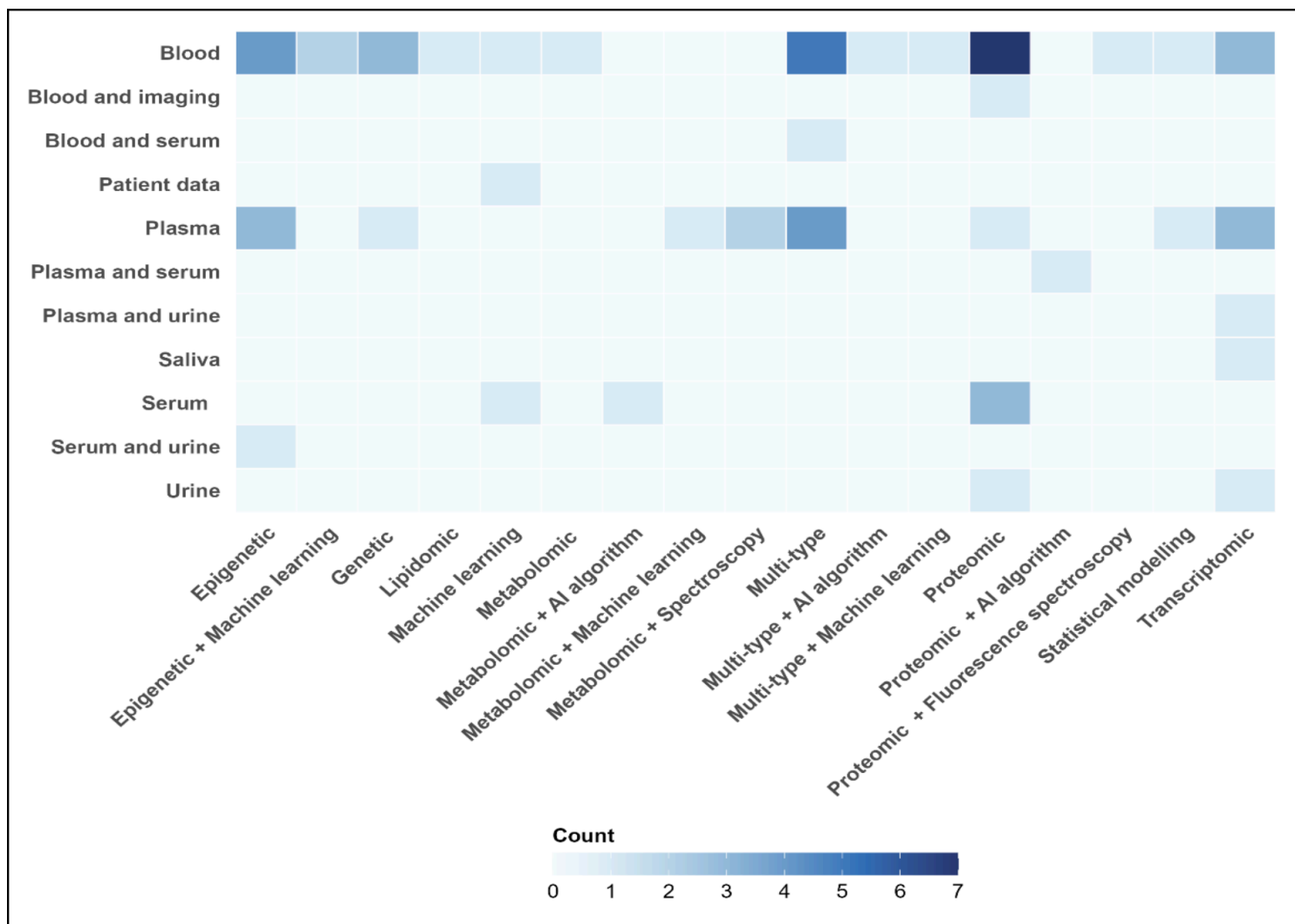


Figure 3

Frequencies of technology applications across different biological sample types recorded in liver cancer.

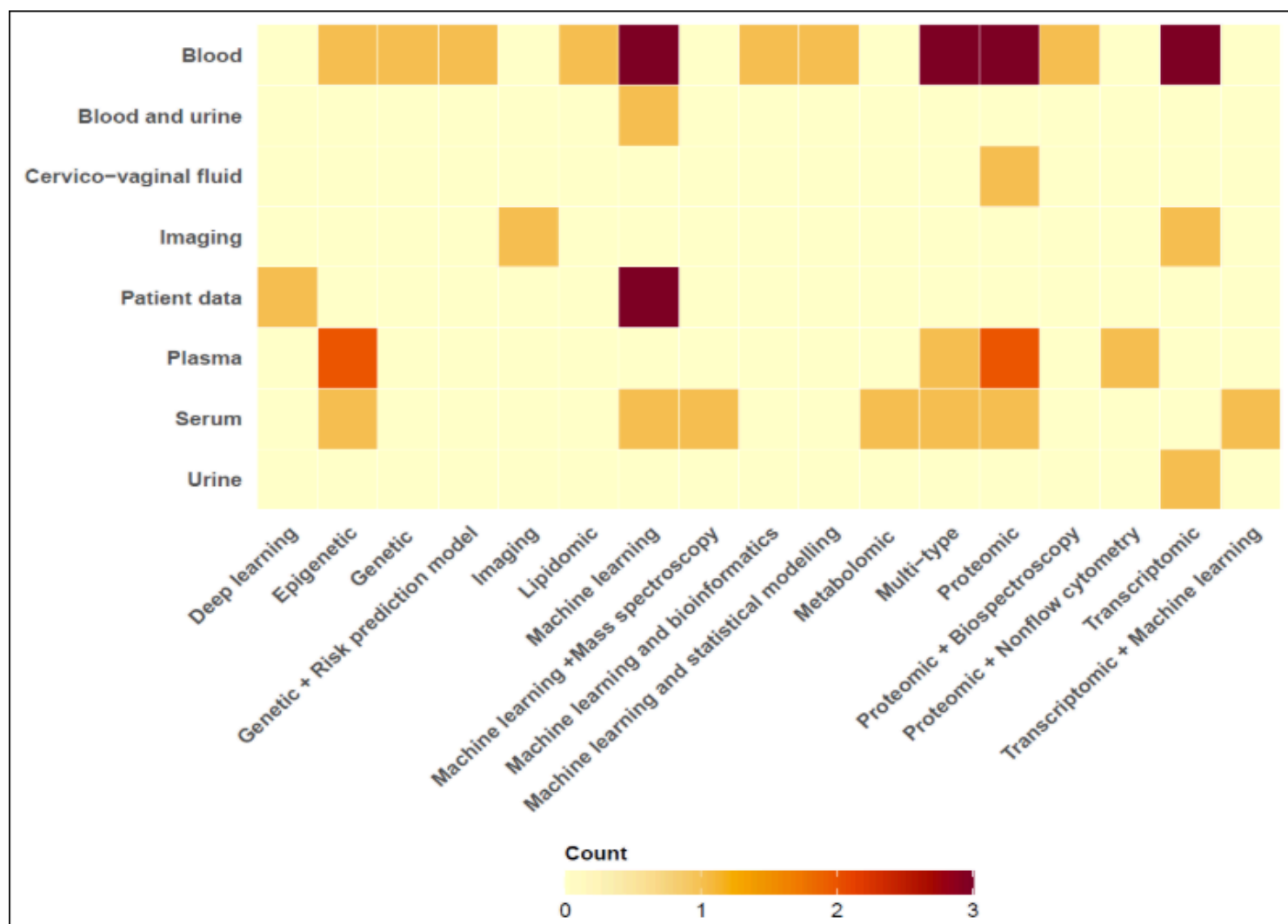


Figure 4

Frequencies of technology applications across different biological sample types recorded in ovarian cancer.

Supplementary Files

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