

Transforming Early Cancer Detection outside Secondary Care Through Emerging Diagnostic Technologies

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Abstract

Background

Early cancer diagnosis is a major health-system priority, particularly for cancers presenting with vague, non-specific symptoms. Current screening programmes remain limited to selected cancers with more site-specific symptoms. Innovative diagnostic technologies may offer opportunities for earlier detection outside secondary care settings. This horizon scan aimed to identify and characterise emerging technologies for the early detection of cancers with generic symptoms for potential use in primary care, community or home-based settings.

Methods

A horizon scanning and evidence synthesis approach was used. Searches were conducted from 2020 in Embase, clinical trial registries, supplemented by relevant systematic reviews, then screened against predefined eligibility criteria to support early cancer detection. Data was extracted on study and/or clinical trial details, technology type, developers, sample or data source, cancer type, and technology readiness level. Findings were summarised descriptively.

Results

After deduplication, 5,293 records were screened, including 4,791 studies and 502 clinical trial protocols. Data extraction was completed for 196 studies, identifying 169 technologies, with 67 targeting generic cancer detection. Most technologies were biomarker-based (n=36), followed by other technologies (n=19), and AI and digital technologies (n=12). Technologies ranged from TRL-2 to TRL-7, with most technologies at TRL-4, indicating early laboratory-stage validation. Blood, plasma and serum were the most common sample types, suggesting stronger suitability for GP or community settings than home testing. A small number of technologies used saliva or urine samples, which may be more compatible with home-based testing. Research activity was concentrated around lung, colorectal, pancreatic, liver, oesophageal and multi-cancer detection. Thirty-one clinical trials for generic cancer detection were identified.

Conclusions

The emerging landscape for generic cancer detection is active but largely early-stage. Biomarker-based and AI-enabled technologies show potential to support earlier diagnosis outside secondary care, although evidence gaps remain around clinical validity, implementation, equity, follow-up pathways and health-system readiness.

Introduction

Cancer is a leading cause of morbidity and mortality globally, placing a significant burden on public health and healthcare systems. Incidence is projected to rise from 20 million cases in 2022 to approximately 35 million new cancer cases predicted in 2050 (1–3). A similar upward trajectory is evident in the UK where cancer cases diagnosed every year are projected to rise by 2% between 2024–2026 and 2038–2040 (4).

This growing burden presents significant challenges to healthcare systems, particularly in terms of escalating costs. By 2050, the global economic cost of cancer is estimated to reach £19.6 trillion (5). Early diagnosis and treatment are known to substantially reduce these costs (6), underscoring the need to strengthen cancer detection and early diagnosis strategies and ensure diagnostic pathways can meet future demand.

Reflecting this priority, Europe's Beating Cancer Plan identifies early detection (alongside prevention, treatment, and quality-of-life initiatives) as a core pillar in addressing the growing cancer burden (7). Similarly, in the UK, the NHS Cancer Plan (2026) highlights the need to improve early diagnosis as a central component of future cancer care (8). However, achieving this goal requires addressing persistent challenges, including reliance on hospital-based diagnostic pathways that contribute to capacity pressures and delays, as well as the clinical difficulty of recognising cancers that present with non-specific or overlapping symptoms (9–11).

Despite this policy focus, current cancer screening programmes to support early detection is limited to a small number of cancer types, and are largely designed for diseases with clear, site-specific symptoms. Across Europe and the UK, screening programmes primarily target breast, cervical, and colorectal cancers (1, 12). Additional initiatives in England and other European countries, such as the Targeted Lung Health Check programme, primary care pilot programmes for liver cancer and EU-wide initiatives like and EUCanSceen (13) extend this scope but remain limited (14). Consequently, many cancers (particularly those with vague, non-specific, or multi-organ presentations) lack efficient or dedicated routes to diagnosis.

Cancer care, including diagnosis, often takes place in hospital settings, placing substantial pressure on secondary care services (15). Primary care, often the first point of contact for patients (16), plays a pivotal role in early recognition, investigation, and referral of suspected cancer (17). thereby relieving avoidable pressure on hospital services. Shifting appropriate elements of cancer detection and early diagnosis into primary care supported by new diagnostic tools and technologies offers an opportunity to reduce the burden on hospitals, shorten time to diagnosis, and improve access for patients who present earlier in their disease course. Expanding diagnostic capabilities within primary care, and potentially into community or home settings, could reduce pressure on hospitals, shorten time to diagnosis, and improve access for patients presenting earlier in their disease course.

Realising this shift will require the integration of innovative diagnostic technologies capable of transforming both how and when cancer is detected. Understanding the current landscape of emerging technologies is essential for informing strategic planning, particularly in primary care, where their adoption could streamline investigation pathways, reduce delays, and improve equitable access. Ensuring alignment between technological innovation and healthcare system priorities will be key to maximising their impact. A clear understanding of these developments is essential to ensuring that future diagnostic technologies are aligned with national priorities and broader healthcare system needs.

Against this backdrop, a structured horizon scanning approach was undertaken to systematically map emerging diagnostic innovations and assess their relevance to future early-detection pathways. Horizon scanning is an umbrella term that is used to describe the systematic examination of information

sources to detect early signs of important developments (18). This paper aims to describe, characterise, and explore potential integration of emerging diagnostic technologies in development for detection and early diagnosis of patients with non-specific cancer symptoms with potential use in primary care, community or home-based settings.

Methods

An evidence synthesis approach was used alongside the horizon scan to combine information from trial registries and academic literature. The horizon scan followed the horizon scanning reporting guidance proposed by Garcia et al.,(19) ensuring consistency and transparency in reporting. A protocol for this study was agreed in advance and published on the Open Science Framework prior to data collection.

We identified emerging technologies in the transitional horizon (5–10 years pre-market access), focussing on technologies which aim to triage patients to a cancer care pathway and can be used outside secondary care such as at home, primary care or in community settings.

Eligibility criteria

Inclusion criteria were defined using the PICOS framework:

- **Population:** Any (children and adults)
- **Intervention:** This focused on technologies designed to support early cancer detection for generic cancer symptoms. The tests may or may not give results instantly. Whilst the sample should be taken in the community setting, the analysis or interpretation of results could be undertaken by specialised staff (e.g., in laboratories or secondary care).
- **Comparator:** Any comparator, including standard care or no comparator.
- **Outcomes:** Overview of the technology, including diagnostic accuracy, setting, use of AI, type of sample if available.
- **Setting:** Tests suitable to be delivered outside secondary care such as at home, primary care setting, or community diagnostic centres (CDCs) which include community healthcare settings, commercial settings or non-acute healthcare provider settings.

Search strategy

A search strategy was developed in Medline (Ovid) and peer-reviewed (Supplementary material 1.1) The strategy was translated to Embase (Ovid) and trial searches were conducted in clinicaltrials.gov and World Health Organization International Clinical Trials Registry Platform (WHO-ICTRP). Date limits of 2020 onwards and English language filters were applied. This date limit was chosen as a pragmatic approach to minimise the volume of cancer related literature whilst capturing technologies still in the transitional phase. Searches were run in October 2025. Reference lists from relevant reviews identified in our search were hand searched to maximise the sensitivity of the search results.

Data collection

Results were deduplicated and uploaded to Rayyan for screening (20). Titles and abstracts of studies were screened independently by reviewers against the inclusion criteria, following an initial consistency check in which 100 studies were jointly reviewed by six reviewers. Full texts were retrieved for those meeting the inclusion criteria and subsequently screened in Covidence (21). Full-text screening was undertaken independently by reviewers, with 10% of eligible articles screened in duplicate to ensure consistency. Any conflicts arising were resolved by discussion among the reviewers. If consensus could not be reached, a third opinion was sought from the researcher/project leads. Once screening decisions were aligned single screening was continued for the remaining records. This was done for both title/abstracts and full-text screening stages. Internal quality appraisal (QA) was completed for both title/abstract and full-text screening as well.

As most studies did not report the intended clinical setting, we used sample type as a proxy indicator, assuming that samples typically collected in primary care or at home (e.g., blood, saliva, urine) were more likely to be compatible with general practice (GP)-based or community-setting pathways.

Data extraction

The final data extraction form consisted of the data fields related to study categories: included patients, technologies, diagnostic accuracy, implementation, and research studies from trial registries. The data was recorded in an Excel spreadsheet. Data extraction was piloted by multiple reviewers until consensus was reached and then completed by single reviewers. Following data extraction, a spot check was undertaken to ensure harmonisation of data, accuracy and consistency. Any discrepancies identified during this process were discussed and resolved through consensus. A 10% sample was double checked by a second reviewer as part of internal QA.

Technology Readiness Level (TRL) measures the developing maturity of certain technologies (22). Information on TRLs was extracted by reviewing each study individually and making an evidence-based judgement about the appropriate TRL classification. We excluded TRL-9 technologies as they fall outside the scope of this review, which focused on emerging technologies.

Data analysis

We consolidated studies by technology into unique entries, grouping multiple studies per technology into a single row with the most recent study as the primary record and earlier studies listed as linked references. Data analysis includes a descriptive overview of the records and research studies from trial registries identified for early cancer detection for generic cancer indications along with trends related to technology modalities and sample types used in them.

For technologies incorporating both biomarkers and other screening modalities (such as AI or imaging), biomarkers were classified using the classification system from the review and terminology describing the additional components of the test was retained as reported. For the purposes of analysis, we further categorised the biomarker only technologies into groups informed by a review article (23).

Results

Identified studies

Following deduplication, 5,293 reports were identified, comprising 4,791 studies and 502 clinical trial protocols (Fig. 1). Data extraction was completed for 196 studies.

Of the 196 included studies, we identified 169 technologies, 67 of which were aimed at generic cancer detection and 102 were for other cancer indications. The analysis presented in this paper is restricted to the generic cancer subset. The remaining studies covering other indications, liver and ovarian cancer, form part of a broader dataset that will be analysed and reported separately.

[Insert Fig. 1]

Figure 1 PRISMA flowchart. Early Cancer Detection Tests (24)

Trial registry landscape

A total of 44 clinical studies were identified, of which 31 were for generic cancers. Figure 2 illustrates further information on these studies. The studies were most frequently conducted in the United States (n = 10), followed by China (n = 8) and the United Kingdom (n = 4), one of which included the UK as a multi-site (Fig. 2a). Most studies at the time were either recruiting (n = 13, 41.9%) or completed (n = 11, 35.5%), with smaller numbers classified as other statuses (Fig. 2b). Sponsor activity was relatively dispersed, although GRAIL, Inc. sponsored the highest number of studies (n = 3), followed by Freenome Holdings Inc., Elypta, Gene Solutions, Shanghai Zhongshan Hospital and Shanghai Weihe Medical Laboratory Co., Ltd. (n = 2 each) as shown in Fig. 2c. Based on reported study end dates, 14 studies were expected to complete in 2026 or later (Fig. 2d).

[Insert Fig. 2]

Figure 2a) Geographic distribution of clinical trials by country b) Recruitment status of identified studies c) Distribution of studies by sponsor d) Number of studies by end date

Technology Readiness Level

Our overall TRL analysis identified technologies spanning TRL-2 to TRL-7, with TRL-7 representing the highest level of maturity and indicating proximity to market and potential implementation (Fig. 3). For generic cancer indications most technologies were classified as TRL-4 (n = 51) which means the technologies is being tested in laboratory setting.

[Insert Fig. 3]

Figure 3 Number of identified technologies by Technology Readiness Level (TRL)

Technology characteristics

Of the 67 technologies identified for generic cancer, 36 were investigating biomarkers only, 12 AI and digital only, and 19 other technologies that included procedures like spectroscopy or cytometry, or where both AI and biomarkers technologies were used together. For AI and digital technologies, terminology was retained as reported in the original studies (e.g. machine learning, artificial intelligence algorithms).

Biomarker technologies

Types of biomarkers constituted technologies such as genes, micro-RNAs (miRNAs), cell-free DNA (cfDNA), matrix metalloproteinases (MMPs), antibodies, antigens and various methylation panels, (Supplementary material 1.2A). Our findings indicate that a substantial proportion of biomarkers being examined are genetic biomarkers within multi-marker panels, such as multiple microRNAs (miRNAs), rather than evaluated as individual, standalone biomarkers. Most biomarker technologies were classified as TRL-4 (n = 29), suggesting that they remain largely at the laboratory validation stage. Only a small number of biomarker technologies were classified as TRL-5 (n = 4), thus validated in a more relevant or realistic environment, but not yet close to routine clinical implementation. Blood-based samples (blood, serum, plasma) constituted the most common sample types utilised (n = 32). Just three of the identified tests

appear to be potentially convenient to be used in a home setting, as two relied solely on saliva samples (Paxillin; and (miR-21, miR-27b, and miR-181b)), and one used urine samples (C. elegans cancer test).

AI and digital technologies

For AI and digital studies, the types of technologies included machine learning models, deep learning models, and statistical modelling algorithms (Table 1). Identified AI & digital technologies (n = 12) in development for generic cancers detection and early diagnosis, with the majority (n = 9) being at TRL-4. Most common type of model used in these technologies is machine learning. As with physical tests with biomarker technologies, blood-based samples (blood, plasma, or serum) were most frequently used. Only three technologies relied on patients’ data with two rated TRL-4 and the other TRL-2. The types used spanned metabolic datasets, presenting symptoms, blood tests, demographic information, and multi-omics data. The aim of these models ranged from cancer subtype discovery, improving cancer diagnostics, and identifying early signals of cancer.

In addition, another technology (deep convolutional neural network algorithm) relied on intraoral photographs of oral lesions to segment oral potentially malignant diseases and oral cancers which is essential for early diagnosis. See Table 1 for further details.

Table 1
Emerging AI & digital technologies being investigated for generic cancers

Test	Sample type/Data source	TRLs
Prediction algorithm(25)	Blood	TRL-5
Machine learning algorithm(26)	Serum	TRL-4
Conditional logistic regression model(27)	Patient data (presenting symptoms, blood tests and demographics)	TRL-4
AutoML-XAI(28)	Data (Metabolic datasets)	TRL-4
Deep convolutional neural network algorithm(29)	Photographs (of oral lesions)	TRL-4
Deep Learning-Assisted Intelligent Artificial Vision Platform(30)	Saliva and serum	TRL-4
Biophysics-based cancer screening method(31)	Blood	TRL-4
Machine learning model(32)	Blood	TRL-4
Circulating miRNA-based MCED model(33)	Blood	TRL-4
Machine learning model(34)	Plasma	TRL-4
Artificially intelligent array of cross-reactive nanomaterial-based chemical sensors + discriminant function analysis (DFA) pattern recognition model(35)	Blood	TRL-3
Statistical modelling(36)	Patient data (multi-omics data from 7 cancer types)	TRL-2
AutoML-XAI= Automated Machine Learning – Explainable Artificial Intelligence; miRNA=microRNA; MCED=Multi-Cancer Early Detection; cfDNA=Cell-free DNA		

Other technologies

Other technologies comprised of procedures like spectroscopy or cytometry, or where both AI and biomarkers technologies were used together (Supplementary material 1.2B). Similar to biomarker-based and AI-based diagnostic tests, most (n = 15) of the technologies used blood, plasma or serum. Only one technology, a combination of a multi-type biomarker panel of 18 metabolites along with machine learning, used a urine sample making it a feasible choice for home testing (37). The technology with the highest TRL (TRL-7) was an AI-enabled exome/transcriptome liquid biopsy platform called Caris Assure (38).

Cancer Coverage in Emerging Diagnostic Tests

We also explored how research activity in generic cancer detection is distributed across different cancer types and diagnostic technologies. Figure 4 shows the distribution of cancer type and technology type for generic cancer detection or early diagnosis. Those studies with more than 20 cancer types targeted were classified as 'multi-cancer'.

[Insert Fig. 4]

Figure 4 Number of technologies using each technology type per specific types of cancers

The highest concentration of technologies was observed for lung, colorectal, pancreatic, liver, oesophageal and multi-cancer cancers, suggesting they are priority targets for both methodological development and clinical translation. In parallel, epigenetic and proteomic biomarkers were the most frequently investigated approaches across these high-activity cancer types, such as, cfDNA 5-hydroxymethylcytosine profiles of long non-coding RNA genes were being analysed for the early detection for colon, gastric, liver, oesophageal, and non-small cell lung cancer.

Technologies adopting machine learning algorithms for AI and digital methods dominated for multi-cancer detection. Interestingly, AI and digital methods were not often identified alone but adopted in multi-modal approaches (e.g. biomarkers integrated with AI) at a moderate frequency, particularly epigenetic biomarkers in combination with machine learning algorithms, reflecting a shift towards more complex AI-driven diagnostic systems. For instance, analysing extracellular vesicle protein with machine learning model. Imaging-based and electronic biosensor technologies were less widely represented across cancer types. For instance, an electrochemical immunosensor for prohibitin 2 is in one clinical study for only blood cancers (39).

Distribution of Technologies by Clinical Use, Setting and Sample Type

We analysed clinical use by care setting, purpose, and sample type (Fig. 5). Most of the technologies were for detection ($n = 44$), followed by early diagnosis ($n = 17$), with few focussed on risk stratification or triage. Sample collection was predominantly hospital-based ($n = 27$), indicating limited deployment in primary care or community settings. Early diagnosis ($n = 17$), particularly within hospital settings, although majority technologies in this stage of clinical use did not report the setting. Figure 5 shows the diverse range of sample types, including plasma, serum, and saliva, suggesting growing exploration of less invasive approaches. Only one test appeared feasible for home use, utilising a dried blood spot sample (40). Primary care remains underrepresented, with just three technologies validated or deployed outside secondary care, highlighting a gap between innovation and system integration.

[Insert Fig. 5]

Figure 5 Distribution of technologies by clinical use, setting and sample type

Discussion

Our horizon scan reveals a rapidly expanding landscape of 67 technologies identified for generic cancer early detection and diagnosis with most innovations focused on biomarker-based approaches. Digital and AI-based tools appear frequently in our horizon scan however remain exploratory in their current stage of development. Understanding these findings highlight both the promise of emerging technologies and the significant evidence gaps that must be addressed before widespread implementation becomes feasible across healthcare systems. Several of these technologies show potential for use in primary care setting or even home or community setting offering potential of earlier cancer diagnosis and management.

Most of the diagnostic technologies identified in our horizon scan relied on blood, serum, or plasma as the primary sample type. A smaller subset of technologies ($n = 9$) utilised non-invasive samples such as saliva or urine, which are more conducive to home-based collection and therefore offer greater flexibility for remote or self-managed testing. Multi-biomarker approaches particularly those incorporating genetic biomarkers such as microRNA, cfDNA, and ctDNA are recurring in the development pipeline. However, the predominance of TRL-4 technologies suggests that much of this activity remains focused on analytical or laboratory-stage validation rather than prospective evaluation in intended clinical pathways. Most AI-enabled technologies in the pipeline were based on machine-learning approaches, reflecting the early exploratory nature of digital diagnostic development, as they have typically been evaluated only in early-stage or retrospective studies with limited external validation.

Earlier cancer detection has the potential to reduce pressures on healthcare systems by lowering demand for resource-intensive treatments, shortening diagnostic pathways, and easing the burden on overstretched specialist services (Fig. 6) (6). However, barriers to uptake are likely to persist. Uptake of screening programmes in the UK remain consistently below target levels for bowel, cervical, and breast cancers, highlighting ongoing challenges in engagement (41). While earlier screening approaches for cancers with non-specific symptoms could improve outcomes, structural and social barriers continue to drive inequalities in early diagnosis.

[Insert Fig. 6]

Figure 6 Shifting from hospital-centric to a potential modernised diagnostic pathway within community or primary care

These barriers include differences in health literacy, ethnicity, socioeconomic status, age, gender, geography and lifestyle choices (42–44). Such determinants disproportionately affect marginalised populations. For example, lower health literacy is more prevalent among ethnic minority groups and those living in deprived areas, while age-related factors such as frailty and reduced mobility can limit timely access to healthcare services (45). In addition, many cancer diagnoses begin in primary care services, yet evidence from UK patient experience data (2011 and 2017) shows that younger patients, ethnic minorities, people living in deprived areas, and sexual minorities report poorer experiences in primary care (45). These disparities may further hinder access to timely investigation and referral, reinforcing inequalities in early cancer detection.

Multi-cancer detection was one of the most active areas identified in this horizon scan (Fig. 4), but these technologies also raise distinct implementation challenges. In established single-cancer screening programmes, follow-up such as colonoscopy for bowel cancer, or colposcopy for cervical cancer (46). In contrast, a MCEd-positive follow-up is more varied in duration and intensity, involving biopsies, CT or MRI scans, respiratory tests, each with different waiting times, preparation equipment and levels of invasiveness (47). Some patients with a positive MCEd test found having to advocate for further tests, justify reasons for presenting to clinicians, and arrange appointments and chase results, highlighting the lack of clear framework for managing positive MCEd tests (48).

Not all MCED technologies target the same cancers (49) which adds to the complexity of MCEDs. Platforms use different biomarkers and molecular signatures, leading to variation in both cancer coverage range and sensitivity. In our analysis, research activity focused mainly on lung, colorectal, pancreatic, liver, oesophageal and multi-cancer detection, while other cancers were less represented. This suggests future research should prioritise not only technologically feasible cancers, but also those with high burden, vague symptoms and limited diagnostic routes.

Despite its transformative potential, AI is associated with a range of ethical concerns, including the risk of amplifying bias. For example, one study found Black patients were disadvantaged by additional care by more than half compared to White patients, as determined by a commercially used algorithm to make health decisions (50). When AI is used in healthcare, patient data must be handled in line with European Union General Data Protection Regulation (51), ethical standards and regional data governance frameworks, (52). Across many health systems, guidance makes clear that algorithms must support, not replace, clinician decision-making, with explicit safeguards around consent, data minimisation, and anonymisation wherever possible ((52).

Many of the AI-assisted tools here would be classed as Software as Medical Device (SaMD). Regulators such as the Medicines and Healthcare products Regulatory Agency now embed transparency, explainability, fairness and governance into the regulatory requirements for SaMD, meaning developers must demonstrate these aspects as part of pre-market evidence and post-market surveillance to maintain safety and public trust (53). Collectively, these frameworks aim to balance innovation with ethical responsibility, clarifying accountability for errors and performance drift, and protecting patient rights while enabling beneficial AI-driven early diagnosis pathways (54).

Strengths and Limitations

To explore emerging diagnostic technologies feasible for use in primary care, community, home settings we adopted a pragmatic search strategy thus prioritising specificity over sensitivity. This approach was chosen in discussion with the wider team in order to combat the significant volume of irrelevant cancer related literature, however, it is acknowledged that some studies may have been missed. The search strategy was peer-reviewed by clinical experts and information specialists to ensure terminology and concepts were appropriate. Publication in English language only were searched which may have resulted in some relevant studies being missed. We also agreed a date limit of 2020 onwards to ensure we captured technologies in early-stage development rather than those already marketed. The team chose core bibliographic databases and trial registries recommended for horizon scanning of medical technologies. Systematic reviews were also hand searched for primary studies. This minimised the risk of missing relevant studies and allowed an iterative accumulation of data.

The included data were subject to several limitations that affect the certainty and interpretability of the findings. Reporting across studies was often incomplete, with insufficient detail on technologies/tests, reference tests. Considerable heterogeneity in study design, sample size, and outcome reporting hindered meaningful comparison across technologies. Additionally, limited availability of data on clinical setting, operator or staff requirements, and cost effectiveness restricted the ability to assess implementation readiness. Importantly, these gaps were present even among late-stage technologies, limiting the usefulness of the evidence base for decision-makers. These constraints should be considered when interpreting the overall evidence base. These gaps highlight the need for a structured framework that developers and horizon-scanning organisations can use to consistently signal the maturity of emerging diagnostic technologies to decision-makers.

Conclusion

This horizon scan is the first of its kind to systematically examine the landscape of emerging technologies, both physical and digital, being developed for the early detection or early diagnosis of cancer. The insights generated have the potential to be highly valuable for anticipating which innovations may be ready for adoption within health systems over the coming years, while also providing a clearer view of the broader development pipeline. This, in turn, can support strategic planning and help health systems plan future uptake including which technologies may be more feasible for use in primary care, community and home settings.

Streamlining diagnostic pathways will require that health systems align technological innovation with workforce capacity, digital infrastructure, and more streamlined referral pathways. Closing the gap between implementation and uptake of diagnostic tests will require sustained public education and targeted behavioural interventions to improve engagement with early detection opportunities. Ultimately, the safe adoption of AI-enabled early cancer detection or early diagnosis in any healthcare system will not be linear and will require strong data governance, clear accountability, and ongoing monitoring to ensure innovation does not come at the expense of equity, patient rights, or public trust.

Abbreviations

ACTB
Actin beta
AFP
Alpha-fetoprotein
AI
Artificial intelligence
ALIX
ALG-2-interacting protein X
ARHGAP35
Rho GTPase activating protein 35

ARID1A
AT-rich interaction domain 1A
AutoML-XAI
Automated machine learning—explainable artificial intelligence
BRCA1
Breast cancer 1
CA125
Cancer antigen 125
CD9
Cluster of differentiation 9
CDCs
Community diagnostic centres
CD01
Cysteine dioxygenase type 1
CE
Cholesteryl ester
CEA
Carcinoembryonic antigen
Cer
Ceramide
cfDNA
Cell-free DNA
cfRNA
Cell-free RNA
CT
Computed tomography
CTNNB1
Catenin beta 1
ctDNA
Circulating tumour DNA
DFA
Discriminant function analysis
DNA
Deoxyribonucleic acid
EGFR
Epidermal growth factor receptor
EU
European Union
EV
Extracellular vesicle
GP
General practice
HDL
High-density lipoprotein
HE4
Human epididymis protein 4
HIST1H4F
Histone cluster 1 H4 family member F
HSPA8
Heat shock protein family A member 8
HSP90AB1
Heat shock protein 90 alpha family class B member 1
HSRIC
Health Services Research and Innovation Centre
hsa-miR
Homo sapiens microRNA
ICTRP
International Clinical Trials Registry Platform
LDL
Low-density lipoprotein

LPC
Lysophosphatidylcholine
LRRK2
Leucine-rich repeat kinase 2
MCED
Multi-cancer early detection
miR
MicroRNA
miRNA
MicroRNA
MMP
Matrix metalloproteinase
MRI
Magnetic resonance imaging
MSN
Moesin
N/A
Not applicable
N/R
Not reported
NHS
National Health Service
NIHR
National Institute for Health and Care Research
PC
Phosphatidylcholine
PhPTz
Poly[(1,4-phenylene)-alt-(3,6-(1,2,4,5-tetrazine)/3,6-(1,2,4,5-dihydrotetrazine))]
PICOS
Population, intervention, comparator, outcomes and setting
PIK3CA
Phosphatidylinositol-4,5-bisphosphate 3-kinase catalytic subunit alpha
PIK3R1
Phosphoinositide-3-kinase regulatory subunit 1
PRISMA
Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PTEN
Phosphatase and tensin homolog
QA
Quality assurance
RAD21
RAD21 cohesin complex component
RAP1B
Member of RAS oncogene family
rGO
Reduced graphene oxide
RNA
Ribonucleic acid
SaMD
Software as a medical device
SERS
Surface-enhanced Raman scattering
SM
Sphingomyelin
SOX7
SRY-box transcription factor 7
SPOP
Speckle-type POZ protein
TC
Total cholesterol

TGL
Triglycerides
TP53
Tumour protein p53
TRL
Technology readiness level
UK
United Kingdom
VLDL
Very-low-density lipoprotein
WHO
World Health Organization
WHO-ICTRP
World Health Organization International Clinical Trials Registry Platform

Declarations

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 the supplementary appendix, see supplementary material 1.3.

Conflicting interests

The authors declare that they have no conflicting interests

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Figures

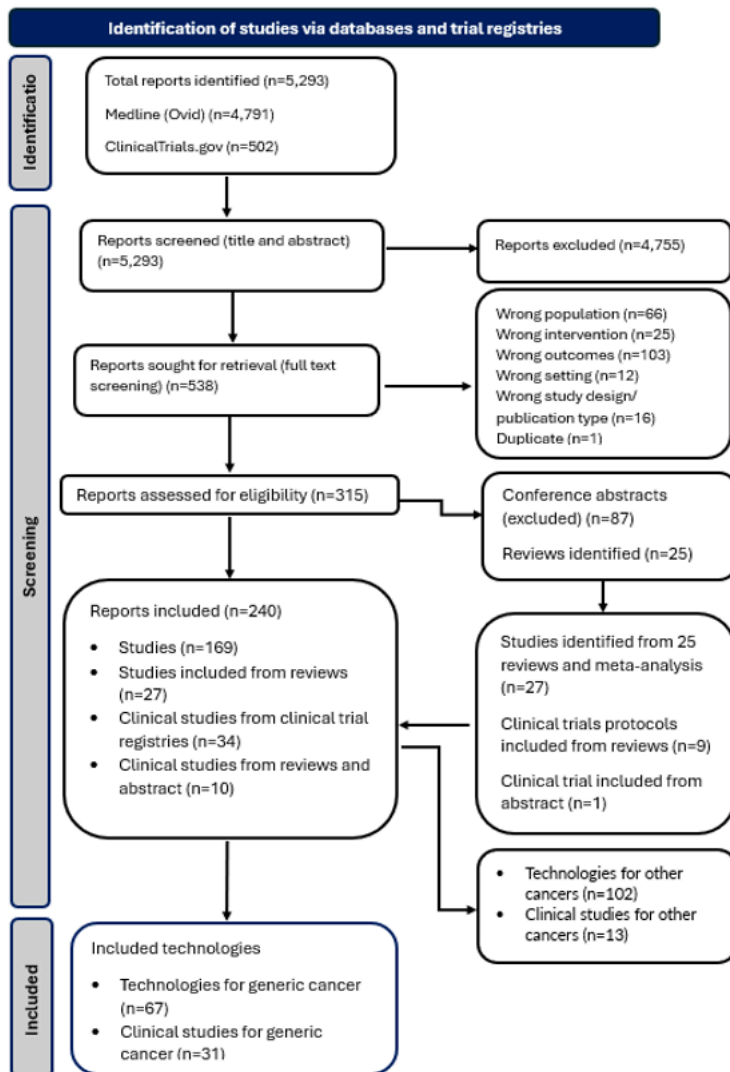


Figure 1

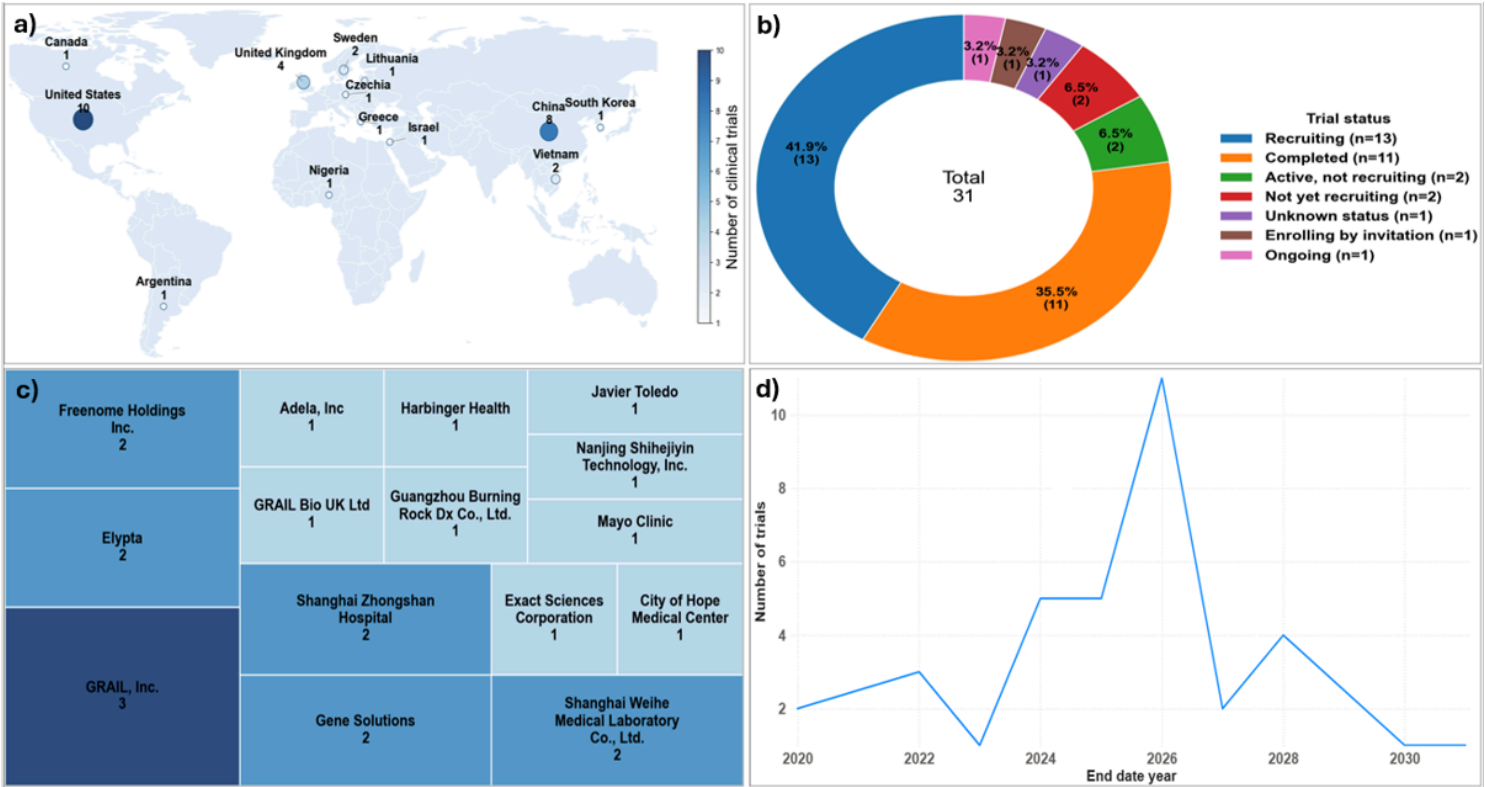


Figure 2
a) Geographic distribution of clinical trials by country b) Recruitment status of identified studies c) Distribution of studies by sponsor d) Number of studies by end date

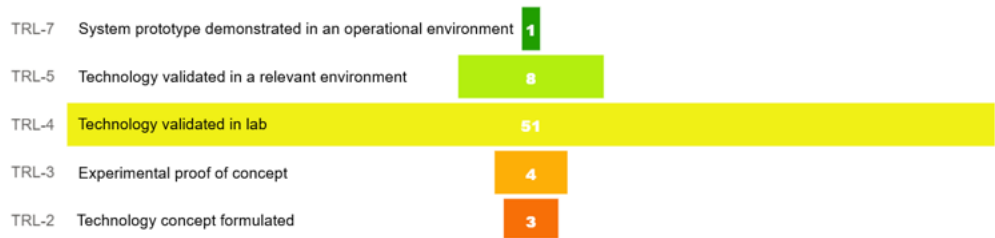


Figure 3
Number of identified technologies by Technology Readiness Level (TRL)



Figure 4

Number of technologies using each technology type per specific types of cancers

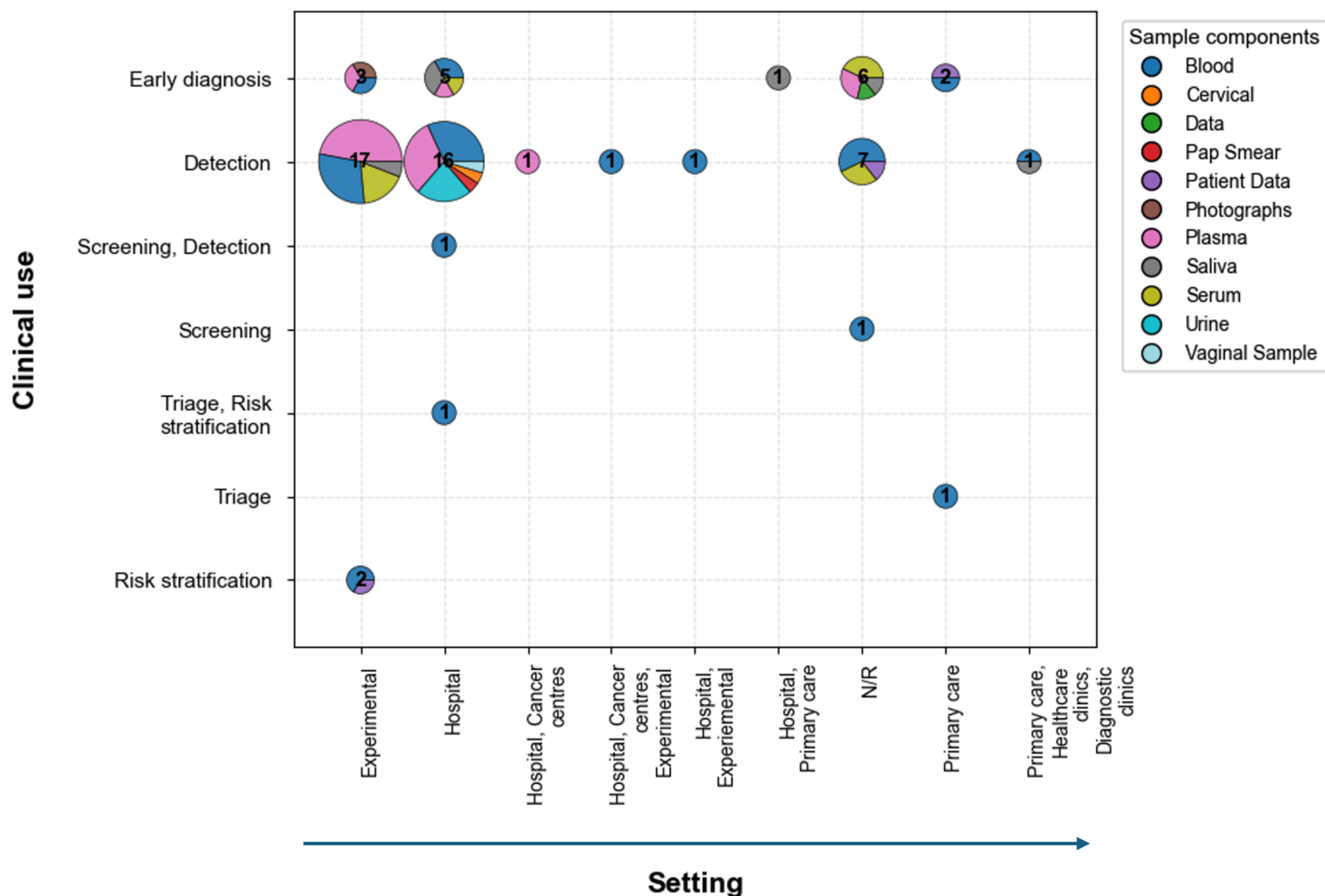


Figure 5

Distribution of technologies by clinical use, setting and sample type

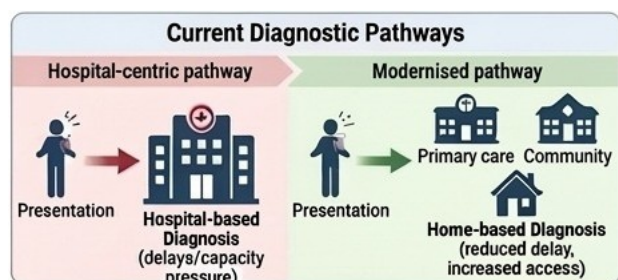


Figure 6

Shifting from hospital-centric to a potential modernised diagnostic pathway within community or primary care

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