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Review Article

AI and omics technologies in biobanking: Applications and challenges for public health

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ABSTRACT

Objectives: Considering the growing intersection of biobanks, artificial intelligence (AI) and omics research, and their critical impact on public health, this study aimed to explore the current and future public health implications and challenges of AI and omics-driven innovations in biobanking.
Study design: Narrative literature review.
Methods: A structured literature search was conducted in Scopus, PubMed, Web of Science and IEEExplore databases using relevant search terms. Additional references were identified through backward and forward citation chaining. Key themes were aggregated and analysed through thematic analysis.
Results: Thirty-seven studies were selected for analysis, leading to the identification and categorisation of key developments. Several key technical, ethical and implementation challenges were also identified, including AI model selection, data accessibility, variability and quality issues, lack of robust and standardised validation methods, explainability, accountability, lack of transparency, algorithmic bias, privacy, security and fairness issues, and governance model selection. Based on these results, potential future scenarios of AI and omics integration in biobanking and their related public health implications were considered.
Conclusions: While AI and omics-driven innovations in biobanking offer specific transformative public health benefits, addressing their technical, ethical and implementation challenges is crucial. Robust regulatory frameworks, feasible governance models, access to quality data, interdisciplinary collaboration, and transparent and validated AI systems are essential to maximise benefits and mitigate risks. Further research and policy development are needed to support the responsible integration of these technologies in biobanking and public health.

1. Introduction

1.1. Biobanks and public health

Biobanks are infrastructures that store biological samples along with complementary data, including health records, lifestyle factors, along with social, cultural and economic information, primarily for medical and health research.[1] According to their scope and sample types, biobanks can be classified as population-, hospital- or health centre-based, or mixed biobanks.[2] Integrated into data-sharing networks and open-access platforms, biobanks enable researchers to share, store and manage biological samples, data and software tools, thereby expanding access to health and scientific expertise.[3]

Biobanks are also powerful facilitators of public health (PH) research through national and international integrated networks, providing timely access to high-quality, well-characterised biospecimens, diverse samples and low handling fees.[4–7] Consequently, biobanks contribute to improve diagnosis, health monitoring and therapy selection,[8] and support health services and the development of effective strategies in the biomedical field.[9] Moreover, biobanks play a pivotal role in shaping PH policy and governance.[4] For example, different biobanks and biobank networks, including the UK Biobank, BBMRI-ERIC and research initiatives, such as NIH's 'All of Us' programme in the US or the European '1+ Million Genomes' initiative, have facilitated the incorporation of

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genomic data into healthcare, shaping data-sharing policies for personalised medicine.[10–12] Similarly, data from the China Kadoorie Biobank (CKB) has provided valuable insights into the relationship between lifestyle factors and chronic disease risk, supporting PH policies focused on disease prevention.[13] Furthermore, biobanks provide an ideal environment for research and application of advanced health-related technologies, such as next generation sequencing (NGS) and cutting-edge medical imaging, in conjunction with health data integration through modern information technologies (IT) tools, including cloud-based research platforms and artificial intelligence (AI).[11,14]

1.2. Artificial intelligence: general classification and health applications

AI refers to the simulation of human intelligence by machines and/or computer systems and can be classified by capability and functionality.[15] According to capability, AI can be classified as: (i) Artificial Narrow Intelligence (ANI), the only existing form, designed for specific tasks, often surpassing human efficiency; (ii) Artificial General Intelligence (AGI), a theoretical AI, capable of learning and performing any intellectual task without human training; and (iii) Artificial Superintelligence (ASI), also a theoretical AI, which could understand and surpass human cognitive abilities, demonstrating emotions, beliefs, desires and judgments.[16] According to functionality, AI can be classified as: (i) Reactive Machine AI, which lacks memory and operates solely on currently available data for specific tasks; (ii) Limited Memory AI, which includes current generative AI (GenAI), using past and present data to improve decision-making over time; (iii) Theory of Mind AI, which is a theoretical AI, capable of understanding human thoughts and emotions for natural human-like interactions; and (iv) Self-Aware AI, another theoretical form of AI, which would be able to recognise its own internal states, emotions, beliefs and desires.[17]

GenAI models represent a significant advancement in AI systems, particularly in natural language processing (NLP). These models use the transformer architecture, which processes sequential data through self-attention mechanisms, enabling better language comprehension and handling of long-range dependencies.[18] Future models are expected to handle multimodal inputs (i.e. text, images, videos and sound), which is crucial for applications in healthcare and PH.[19] Multimodal AI is especially valuable for replicating the diverse inputs used by clinicians and healthcare administrators in decision-making.[20] Recent health applications include precision medicine, digital clinical trials, remote monitoring, pandemic surveillance, digital twin technology and virtual health assistants.[20,21]

In recent years, the availability of health-related data combined with the computational power of modern IT solutions, such as AI, has fuelled complex big data research, with omics research as a prominent example. Omics research focuses on the comprehensive study of the totality of specific molecules in an organism, including genomics (DNA), transcriptomics (RNA), proteomics (protein), metabolomics (metabolites) and others.[22] Furthermore, these disciplines can be integrated with the study of environmental exposures ('exposomics'), promoting complementary developments between biomedicine and PH due to their interconnected pathways.[23,24]

Given the growing intersection of biobanks, AI and omics research, and their critical impact on PH, this study conducted a review of the existing literature to explore the current and future PH implications and challenges of AI and omics-driven innovations in biobanking.

2. Methods

This study presents a literature review based on a two-step methodology. The first step consisted of a literature search using various combinations of search terms, categorised according to the main research fields and keywords of articles ("biobanks", "omics", "artificial intelligence" and "public health") in Scopus, PubMed, Web of Science and IEEExplore online databases (see Appendix 1 in the supplementary material). The search terms were derived using the PI(C)O (Population, Intervention, Comparison, Outcome) framework[25] for the following research question: *What are the current and future public health implications and challenges (O) of AI- and omics-driven innovations (I) in biobanking (P)?*

This search included original research papers, review articles, technical reports and policy reports, published in English between 2014 and 2024. Article selection was conducted by the authors based on relevance and content connections across the research areas. Subsequently, a complementary reference search was conducted using backward and forward citation chaining. Key themes were identified and aggregated into categories through thematic analysis.[26]

Thirty-seven studies were selected for analysis (Appendix 2), leading to the identification of the following three major categories of influential developments arising at the intersection of AI, omics and biobanking in PH: (i) advancements in high-throughput sequencing; (ii) advanced diagnostics and therapies; and (iii) pattern recognition and predictive analytics. This article selection and categorisation approach provided a summary of the research field, helping to identify key challenges and explore potential future scenarios.

3. Overview of recent advances in AI for biobanking and public health

3.1. High-throughput sequencing and data generation

In recent decades, the exponential growth rate for reducing nucleic acids sequencing costs has outpaced Moore's Law, which states that computer systems' power for calculus roughly doubles every 2 years.[27,28] In the context of biobanking, the recent integration of AI and genomics has accelerated research through task automation,[29] enhancing result interpretability through deep learning architectures that hierarchically organise and correlate interconnected data.[30]

High-throughput sequencing (HTS), such as next- and third-generation sequencing technologies, applied in biobanking have generated significant volumes of data, enabling the identification of new genetic and epigenetic mutations, improved understanding of genetic regulatory processes, broader assessment of gene expression patterns, and the exploration of relationships between genetic variants and diseases through enhanced phenotypic and genotypic correlations, all of which have significant potential PH impacts.[31] In particular, HTS has been crucial for mapping genetic mutations in primary cancers, leading to the development of targeted therapies and personalised treatments.[31] Furthermore, HTS has been useful for the surveillance of infectious diseases, such as COVID-19, by enabling the identification and tracking of the different virus variants worldwide, contributing to improve PH responses and vaccine development.[32] Finally, HTS and biobanking research have improved diagnostics of rare genetic disorders, such as hereditary macrothrombocytopaenia, and provided revised guidance for patient-specific treatments for various diseases, including cancer or neuropsychiatric disorders.[31]

In summary, HTS in biobanking has strengthened PH by improving efficiency, refining result analysis and interpretation, and improving disease diagnostics, therapy and surveillance.

3.2. AI-driven diagnostics and therapies

Developments in computation and multimodal AI algorithms, alongside the increasing volume of available biobank data, enables the development of diagnosis and therapy pathways, including the design of protein machines with complex specific functions, or even the design of new synthetic organisms.[33]

Proteomics, which is the large-scale study of proteins using mapping of an analytical technology, such as *de novo* protein synthesis or mass spectrometry, has also benefited from the use of AI in the context of biobanking.[34] This integration has driven significant progress in drug development and biomarker discovery.[34,35] For example, AlphaFold is an AI programme that predicted protein structures with significantly more accuracy than the next best IT system, rendering it comparable to experimental methods.[36–38] Notably, in 2022, the AlphaFold Structure Database grew from 1 million protein structures to 200 million, which is roughly the total number of proteins known.[39] In the context of biobanking, AlphaFold is also identifying potential post-translational modification (PTM) sites, streamlining the identification of likely PTM sites for experimental validation, which has PH implications, including disease modelling and therapeutic target identification.[37] New therapies are emerging through an acceleration in AI-driven drug discovery research, promising to enable complex treatments in medical areas, such as oncology, that show great data heterogeneity between patients (and sometimes within the same patient).[40]

In parallel, gene editing therapy is an example of the combined capability to read and decode genetic information with the power of editing the genome. This enables significant possibilities for PH applications.[41] Despite being performed since the mid 1980s, the revolutionary Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) Cas9 technology significantly enhanced gene editing precision, with ongoing trials for clinical applications.[42] As an example of the accelerated bench-to-bedside pipeline with biobanking research playing a crucial role, CRISPR/Cas9 gene therapy was recently approved.[43]

However, although CRISPR-based gene editors are powerful, they present limitations in specificity, sequence targeting, reliance in cellular endogenous double strand-break (DSB) repair and problems with the delivery vectors to target cells.[44] In addition, AI can enhance precision and efficiency through predictive modelling by designing gene editors that show comparable or improved activity and specificity with prototypical gene editors, thus minimising off-target effects.[44,45]

3.3. Pattern recognition and predictive analytics in public health

AI applications in omics can optimise and accelerate drug discovery and design by improving the prediction and the selection of the best suited candidates through the analysis of large datasets.[46] Deep Learning (DL) algorithms have emerged as a powerful tool in multi-omics data analysis due to their ability to process complex, nonlinear and hierarchical features, facilitating biomedical research through the explanation of complex molecular interactions.[47] AI tools have also proven beneficial in statistical analysis of large datasets, and the construction of predictive models with positive PH implications.[48,49] Classical statistical models widely used in epidemiology can be complemented with novel AI models through improvements on big data analysis with high dimensionality.[50] AI can also improve omics data classification and prediction tasks, albeit challenged by explainability.[30] Nonetheless, it is imperative for researchers to objectively choose the correct statistical tool to avoid biased outcomes and unreliable results, especially when validating AI models.[48] Through improved pattern recognition and predictive analytics, multimodal AI can impact various research fields, such as personalised medicine and precision public health (PPH), by promoting the integration of clinical and genomic data, improving the extraction of features from extensive clinical text data and images, performing complex gene model analysis, identifying hereditary patterns, detecting omics-related disorders, facilitating customised screening options and treatment recommendations, and identifying novel therapies.[29,51]

4. AI and omics in biobanking: prospects and challenges

4.1. Potential benefits and transformative impact

Adoption of AI in PH is transforming many areas, including spatial modelling, geographic tracking, risk prediction, PH surveillance, diagnostics, disease complication prediction and epidemic modelling.[9,52] This was particularly evident during the COVID-19 pandemic, which accelerated the implementation and expansion of AI in PH.[52,53] Furthermore, the COVID-19 pandemic highlighted the critical importance of biological samples in the rapid development of effective vaccines to combat infectious disease outbreaks, as well in identifying and studying the long-term effects of COVID-19.[54,55] Moreover, the intersection of AI, omics and biobanking is supporting significant PH advances, including the detection of relevant human malaria species, identification of disease susceptibility variants, development of polygenic risk scores for different conditions and rapid protein identification in the context of antimicrobial resistance.[6,7,53,56] This growing analytical capacity has also driven the emergence of concepts like PPH, which refers to the growing use of biological and genetic data from large populations to inform and guide PH assessment policy design and implementation measures.[57,58] In this context, omics sciences play a crucial role in preventing both communicable and non-communicable diseases by enabling health status assessments throughout an individual's life.[51] Consequently, significant population health improvements can be achieved by implementing omics tools for everyone.[59]

In the future, it is fundamental to optimise biobank infrastructures to fully harness the potential of AI for biological structure prediction, advancing research on complex biological regulatory mechanisms, and further translating molecular insights into knowledge-based PH strategies.[60] In parallel, the standardised assessment of medium-to long-term effectiveness of omics-based AI applications, along with efforts to strengthen global health equity and quality is key. Achieving this will require scaling technologies for implementation in low-resource settings.[61] Scalability can be achieved through different approaches, including optimising local resources for cost-effectiveness and sustainability, fostering international collaborations to share knowledge, resources and infrastructure, standardising cross-border data collection and storage with cloud-based solutions and efficient AI models, and investing in training of researchers and healthcare workers. These approaches will enable more accurate diagnosis, personalised treatments, enhanced outbreak detection, improved disease surveillance, reduced healthcare disparities through equitable access to advanced technologies, and sustainable improvements in overall health outcomes.[14,61,62]

4.2. Technical, ethical and implementation challenges

Although the use of multimodal AI in biobanks health data holds great promise and is already delivering valuable results, there are challenges to consider. One key technical challenge is the selection of appropriate context-specific AI algorithms, be it task-specific or foundation models, and incorporating varying levels of supervision for optimal performance considering the sheer volume and complexity of the omics data being generated, combined with the heterogeneity of complementary data.[63–67] Additionally, data accessibility, variability and quality remain critical concerns as AI models rely on comprehensive, standardised and rigorously-curated datasets to ensure generalisability and to provide rigorous and reliable insights.[68,69] Ensuring robust validation methods is also essential, requiring standardised methodologies to assess model accuracy, generalisability and reproducibility across different biobank datasets.[70]

Balancing system performance with interpretability, safety and security is crucial as large, complex AI models often lack explainability, which are essential for clinical validation and successful real-world implementation.[70] Consequently, PH applications of AI-driven omics-based research require significant efforts to guarantee result interpretability and explainability.[71,72] This includes clinical validation, minimising false positives and negatives, and establishing professional standards for interpreting and communicating risks to patients and the public.[21,73,74] Furthermore, the use of AI in predictive analytics and pattern recognition in PH poses additional challenges, including accountability for AI-driven decisions, over-reliance by health professionals that may compromise autonomy and human oversight, risks associated with poor data quality and under representativeness, and a lack of transparency, often referred to as the 'black box' problem.[73,75] There are also ethical concerns surrounding AI in healthcare and PH, including population discrimination due to biased and overly predominant data sources, data privacy issues, and the potential exacerbation of existing inequities.[75] Additionally, the risks of extrapolating AI-driven conclusions from unsound or overrepresented data should not be overlooked, as this may lead to the misinterpretation of AI outputs as infallible evidence. Such misconceptions can contribute to flawed decision-making across various applications and reinforce existing biases in healthcare and PH.[76] Addressing potential algorithmic biases requires a combination of strategies, including data preprocessing techniques, such as the following: normalisation, standardisation or anonymisation; ensuring algorithmic transparency and explainability; promoting diverse and balanced populational representation; fostering interdisciplinary collaboration and incorporating human oversight in AI decision-making; establishing ethical frameworks for responsible development and implementation of AI; and implementing continuous monitoring and follow-up of AI performance throughout its lifecycle through internal and external audits.[75]

Many of the challenges posed by AI in public biobanking are not new.[77] Designing and deciding on the appropriate informed consent models that balance individual autonomy with public interest, while ensuring special protections for vulnerable groups and enabling rapidly evolving PH research remains an issue.[78] Furthermore, integrating multimodal data, including citizen-generated data, demands privacy safeguards to prevent unwanted stratification and profiling. Although privacy issues have long been discussed in biobanking,[79,80] AI-driven advancements have intensified the debate.[81] Additionally, questions of data and sample ownership, along with security considerations, continue to present ethical and legal challenges.[82] While recent studies highlight the fluency, flexibility and originality of GAI models, multimodal AI applications in PH biobanking must prioritise scientific accuracy and robustness.[83] Responsible AI adoption requires collective efforts, as AI advancements in this context depend not only on omics data availability but also on broad knowledge accessibility. This 'democratisation of knowledge' relies on multidisciplinary collaboration and structured accessible knowledge representation to drive progress in different PH disciplines.[84,85] However, safeguarding fundamental rights, such as personal and familial privacy, dignity, personal choice and non-discrimination, may become increasingly challenging as data integration and sharing intensify in biobanking.[81,86,87] Striking the right balance between these values while maintaining transparency and explainability is essential for fostering public trust, involvement and participation in AI-driven PH biobanks.[88]

Regulatory frameworks play a crucial role in balancing patient and public safety with innovation. For example, the number of AI-enabled medical devices and algorithms authorised by the US regulator has been growing,[89] primarily in radiology, cardiology, neurology and haematology.[90] Concerns over the concentration of power in large technology companies continues to grow, while governments worldwide, including in the EU, US, UK and China, have implemented AI regulations to varying extents, focusing on risk categorisation, fairness, transparency, safety, privacy, non-discrimination and explainability in healthcare and PH.[91–95] However, while smart regulation is essential, fully harnessing the potential of omics and AI in biobanks for PH requires optimising the use of IT resources and designing adequate and effective governance models.[14,96,97]

In conclusion, multimodal AI integration in PH biobanking elicits significant technical, ethical and implementation challenges.[98–100] The selection of appropriate AI models plays a crucial role in ensuring accuracy, robustness and fairness. Additionally, data ethics issues, including privacy, security, ownership, access, bias and transparency, become even more critical in this context, along with their broader impact on trust and integrity.[101] Addressing these challenges requires well-designed governance models that guarantee participatory PH biobanking, while balancing private and public interests to responsibly maximise the enormous potential of multimodal AI for PH.[21]

5. Discussion

The global healthcare AI market is expected to grow due to a variety of factors, including venture capital investments, increasing demand for precision therapies, the need to reduce costs in health systems, and the increase of high volume, high complexity datasets.[102]

Considering that important sociotechnical AI challenges are likely to be met with increased AI sophistication and wider AI adoption in practice,[18] this study anticipated possible future PH scenarios facilitated by the intersection of AI and omics in the context of biobanks[103] (see Table 1). The scenarios are laid out on a framework designed to discuss the impact of disruptive technologies on future social changes, considering economic, environmental, social, political and governmental dimensions.[104] PH scenarios included in the Gradual Optimism cluster result from the notion that humans will have the capacity to control AI technology positively through choices and gradual changes, framed in the perception that AI and technology in general are considered part of a social construct. PH scenarios included in the Disruptive Pessimism cluster, result from the idea that AI technology will induce disruption and disorder in society, leading to specific changes within a strong deterministic perspective. PH scenarios included in the Contingent Optimism cluster, stem from the notion that AI technology may positively influence society, considering its social context, in a less deterministic and gradual way while considering its limitations, which require political and governmental management. Finally, PH scenarios included in the Pessimistic Social Shaping cluster include the perspective that AI technology will amplify existing social changes, enhanced by trending economic polarisation.

The use of AI and omics technologies in biobanking for PH has driven social and cultural development, yet its implementation also challenges our collective capacity to minimise inequalities in healthcare access, mitigate social and cultural divisions, and address power imbalances.[105] Maximising practical applications while minimising negative impacts is complex and unlikely to have a simple, universal solution, particularly on a global scale. To ensure the feasibility of governance models across diverse socio-economic contexts, it is crucial to consider local resources, regulatory landscapes and infrastructural capacities.[106]

Regulatory agencies and governments face increasing pressure to adapt policies and guidelines in response to the rapid advancements in AI and omics. Two major aspects challenge the current regulatory landscape. First, a strong investment in AI combined with its capacity to deliver fast and complex analysis accelerates adoption, potentially creating gaps in regulatory frameworks and increasing risks for research and health applications.[107] Second, technical concerns regarding reduced human oversight and understanding of algorithmic data processes and conclusions highlight the need for mitigation strategies, such as explainable AI, model transparency, ethical AI frameworks or the inclusion of human-in-the-loop mechanisms.[108] Addressing these challenges will be crucial for ensuring responsible and equitable implementation of AI-driven biobanking in PH.

Broad collaborative efforts among key stakeholders can support responsible integration of these complex technologies in the health sector.[105] However, increasingly diverse and heterogeneous global regulatory frameworks for these technologies may be counterproductive, creating confusion and uncertainty.[109] Alternatively, engaging stakeholders to freely introduce and adapt key consensus methodologies in a practical and flexible bottom-up approach, could complement the design and execution of top-down regulation-based frameworks.

The most consensual elements across multiple regulatory frameworks include data security, quality, validation procedures, accountability and the protection of common ethical values.[110] One fundamental process that can address these issues and be adaplable to the particular requirements of different technological systems or research environments is risk assessment. Integrating risk assessment of

Table 1
Potential public health scenarios arising from the intersection of AI and omics technologies in biobanking for public health. The framework and clustering are based on Choi and Moon.[104]

Clusters	Most relevant developments influencing possible scenarios	Possible Scenarios
Gradual Optimism	High-throughput sequencing and data generation	• Ubiquitous possibility to store and manage individual biological samples and health data in biobanks. Development of international governance standards safeguarding individual rights for data and sample safety, security, informed consent and confidentiality.
	AI-driven diagnostics and therapies	• Improved public health systems via easier access and processing ability to analyse and interpret biobank big health datasets with AI. Development of comprehensive ethical, legal and quality frameworks for researchers and developers to improve algorithm transparency, explainability and generalisability, reducing bias and engaging confidence among stakeholders.
	Pattern recognition and predictive analytics in public health	• PH will gradually acquire deeper and stronger granularity, with the increasing ability to collect, store, process and interpret large volumes of omics related health data with great speed, using AI. Health Authorities will be able to continuously monitor health status in real-time, being able to rapidly identify early signs of outbreaks, predict onsets and develop tailored precision PH actions.
Disruptive Pessimism	High-throughput sequencing and data generation	• Individual private and personal biological data is owned and managed by centralised technological entities, prioritising technological development versus individual rights. Highly technological deterministic scenario where governance has no real influence.
	AI-driven diagnostics and therapies	• Increasingly automated and data-driven health services, favouring mechanistic health systems, with a prominent artificial/synthetic overall environment, detrimental to a more organic/humanistic one. Human subjects become less influent as advanced technologies like AI lead the development, implementation and deployment of clinical applications. Highly technological deterministic scenario with no account for relevant governance influence or regulation.
	Pattern recognition and predictive analytics in public health	• Social segregation/stratification based on individual health data stored and managed in biobanks. Increased disparities in PH access in different socio-economical landscapes and geographies. Highly technological deterministic unregulated healthcare scenario.
Contingent Optimism	High-throughput sequencing and data generation	• Open-source supervised biobank data sharing networks for PH research. Development of generalized collaborative standardised models of governance from stakeholders of different institutions, aiming for equitable access to data and samples from biobanks, complying with transversal ethical and legal regimens for collection, storage and sharing.
	AI-driven diagnostics and therapies	• Creation of international regulation/guidelines that frame AI and biobank omics related activities, to best suit (public) health systems. International standardised guidelines facilitate and ensure that AI and omics research is adequately conducted and deployed in real world clinical settings addressing quality, transparency, efficiency, effectiveness, ethical and legal requirements, for the benefit of PH.
	Pattern recognition and predictive analytics in public health	• The demand for improved public health emergency surveillance, planification and action, by resorting to biobanks data analysis with AI, will challenge governments' ability to adequately implement policies and regulations that allow technological developments to improve PH and simultaneously safeguard individual and collective rights.
Pessimistic Social Shaping		Rise of a biobank and/or health data technological monopoly/oligopoly, that overruns government's ability to regulate or control its activities:
	High-throughput sequencing and data generation	• Biobank samples, datasets and activities are managed by non-governmental trans-national privately owned self-regulated companies, that drive technological AI/omics research and development towards shareholders' interests, detrimental to the general population or state governments.
	AI-driven diagnostics and therapies	• Governments become users/clients to a type of 'global health data feudalistic system' owned by large international health technology companies, subscribing rights for populations PH services, amplifying access discrepancies and inequalities.
	Pattern recognition and predictive analytics in public health	• Ranking access to health technologies via social-economic status or health data profiling, and the creation of separate healthcare niches, transitioning from a global public health perspective to a more stratified *common health* approach within each stratified group.

AI, artificial intelligence.

AI and omics applications in biobanking throughout the entire research lifecycle could help prevent or minimize imbalances between valuable innovation efforts and potential side effects, improve health outcomes and support evidence-based PH policy.

5.1. Conclusion

The intersection of AI and omics technologies in biobanking holds significant potential to deliver improved and faster PH outcomes at a global scale. AI-driven multi-omics analysis in the context of biobanks can enhance early disease detection, diagnostics and therapeutics, while also informing prevention strategies through precision medicine. Additionally, AI-assisted pattern recognition and predictive analytics allow insights into communicable and non-communicable disease mechanisms, supporting biomarker discovery, risk assessment and large-scale population health studies.

However, this potential comes with significant challenges. Beyond socio-economic, financial and political disparities that drive inequalities in access and representation, there are technical, ethical and implementation issues to consider. Key issues include data quality, algorithm choice and validation, transparency, data privacy and security, bias and discrimination, regulatory and governance frameworks, and stakeholder's accountability. Accounting for socio-economic diversity and fostering long-term inclusive collaboration among stakeholders may facilitate successful implementation of AI-driven biobanks with evidence-based PH impact. Lastly, developing interconnected and dynamic governance and regulatory frameworks that adapt to different scientific contexts should provide a suitable foundation for responsible and technically robust development of AI and omics-driven biobanking initiatives that effectively serve all stakeholders in PH.

Author statements

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Competing interests

The authors have no competing interests to declare.

Appendix A. Supplementary data

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