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SUSTAINABLE PUBLIC HEALTH SOLUTIONS THROUGH THE INTEGRATION OF BIOTECHNOLOGY AND ARTIFICIAL INTELLIGENCE

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ABSTRACT
This study explores the transformative potential of integrating biotechnology and artificial intelligence (AI) in developing sustainable public health solutions. Recent advancements in biotechnology, including protein engineering and genetic manipulation, have led to innovations in drug discovery and personalized medicine. However, the challenges of rising competition and the need for comprehensive clinical trials necessitate continuous innovation. AI technologies, particularly machine learning and deep learning, enhance the analysis of complex biological data, enabling precision medicine and optimizing drug development processes. This research examines how the synergy between biotechnology and AI can address critical public health issues, including disease prevention, vaccine development, and environmental sustainability. The study highlights the potential of AI to revolutionize vaccine discovery and drug development, significantly reducing timelines and costs while improving efficacy. However, the integration of AI in public health faces challenges such as data bias, accessibility, and regulatory hurdles. Addressing these challenges requires interdisciplinary collaboration, ethical frameworks, and investments in local expertise. By leveraging AI-driven innovations, particularly in low- and middle-income countries, the study emphasizes the importance of fostering a more equitable global health landscape. Ultimately, this research underscores the need for a collaborative approach to harness the full potential of biotechnology and AI, paving the way for effective and sustainable public health solutions.
KEYWORDS: Biotechnology, Artificial Intelligence (AI), Public Health, Sustainable Solutions, Drug Discovery, Vaccine Development, Environmental Sustainability, Health Equity, Data Bias, Ethics in AI

1. Introduction

The intersection of biotechnology and artificial intelligence (AI) has the potential to revolutionize public health by offering sustainable solutions to complex medical challenges. Recent advances in biotechnology have driven innovation in drug discovery, personalized medicine, and biologics manufacturing through techniques such as protein engineering, genetic manipulation, and advanced cell culture technology (Mudunuri, Yalampati, Voosala et al., 2024). These advancements have enabled the development of sophisticated medicinal solutions, including stable and effective small-molecule formulations, which are widely used in pharmaceuticals due to their cost-effectiveness and simplicity in chemical synthesis. However, the increasing competition among novel small molecules and the demand for comprehensive clinical trials present financial and operational challenges for pharmaceutical companies, necessitating continuous innovation (Dickherber et al., 2015; Troiano et al., 2016; Colombo et al., 2018; Al-Zahrani, 2024; Suriyaamporn et al., 2024; Ali et al., 2024).

In response to these challenges, the biopharmaceutical industry is experiencing rapid growth, especially in the field of biomolecular drugs, which consist of complex biological macromolecules such as nucleic acids and proteins. These biomolecules, including successful examples like adalimumab and insulin, offer unique therapeutic benefits but also present challenges related to stability, pharmacokinetics, and delivery mechanisms (Chavda et al., 2023). The advancement of nucleic acid-based therapies, for example, requires

solutions to enhance molecular stability and optimize pharmacokinetic exposure. This necessitates innovative technologies and novel delivery systems to improve efficacy and patient outcomes (Ali et al., 2024; Li et al., 2024; Bentele & Weder, 2024; Shang et al., 2024).

Simultaneously, AI has emerged as a transformative force in biotechnology, enabling breakthroughs that were once unimaginable by leveraging advanced computational techniques and vast datasets (Nunavath & Nagappan, 2024). AI systems, including machine learning (ML) and deep learning (DL), have reshaped traditional biotechnological approaches, facilitating data-driven discoveries in genomics, proteomics, metabolomics, and pharmacogenomics (Xiao et al., 2021; Mund et al., 2021; Petrick & Shomron, 2022; van der Lee & Swen, 2023). With its capacity to analyze complex biological data, identify patterns, and make accurate predictions, AI has the potential to significantly enhance public health strategies by enabling precision medicine, optimizing drug development processes, and promoting proactive disease management (David et al., 2021; Diaw et al., 2022; Caudai et al., 2021; Lin & Ngiam, 2023).

The integration of digital technologies is fundamental to the application of AI in biotechnology. Digital transformation facilitates the collection, storage, analysis, and sharing of vast biological datasets, which are crucial for AI systems to function effectively (Holzinger et al., 2023). Biotechnology companies and healthcare organizations globally maintain extensive databases that support critical processes such as drug manufacturing, chemical analysis, RNA and DNA sequencing, and enzyme studies. By automating tasks and minimizing human error, AI-driven digital solutions can enhance the efficiency and accuracy of research and development in biotechnology, ultimately leading to faster and more precise public health interventions.

Digital transformation in biotechnology not only enhances operational efficiency but also enables disruptive innovations by leveraging big data and AI analytics. This paradigm shift has paved the way for advanced biotechnological applications, including precision medicine, genomic editing, and the design of personalized therapeutic solutions (Schork, 2019; Aguilar-Gallardo & Bonora-Centelles, 2024). The integration of AI with other digital technologies, such as cyber-physical systems and advanced sensors, further accelerates the automation of complex bioprocesses, ensuring sustainable and scalable solutions for public health challenges.

AI's transformative impact on biotechnology is evident in its applications across various domains, including drug discovery, biomolecular engineering, personalized medicine, and genome editing (Berente et al., 2021; Bhardwaj et al., 2022). By enabling the analysis of large-scale data from genomics, proteomics, transcriptomics, and metabolomics, AI enhances the accuracy and productivity of scientific research, facilitating the development of innovative public health solutions. For instance, AI algorithms can predict disease outbreaks, optimize vaccine design, and support the development of targeted therapies, thus promoting proactive and preventive healthcare strategies (Castro & New, 2016).

Furthermore, AI's role in environmental and marine biotechnology presents sustainable public health opportunities through advancements in biodiversity preservation, pollution mitigation, and bioremediation (Lescrauwaet et al., 2022). Thus, leveraging AI-driven biotechnological innovations, it is possible to address global health challenges such as food security, waste management, and environmental sustainability. However, despite its potential, AI in biotechnology faces significant challenges, including ethical concerns related to data privacy, algorithmic transparency, and socio-economic implications of genetic editing. Ensuring the reliability of AI models to predict complex biological outcomes and establishing ethical guidelines are essential for the responsible deployment of AI in public health solutions.

1.2. Scope and Objectives of the Study

This study aims to explore the integration of biotechnology and AI as a pathway to sustainable public health solutions. It investigates how advanced biotechnological innovations, powered by AI, can address pressing public health challenges, including disease prevention, personalized medicine, and environmental sustainability. However, examining the transformative potential of AI in enhancing biotechnological

applications, this study seeks to provide a comprehensive understanding of how this interdisciplinary approach can revolutionize public health strategies.

2. What is Artificial Intelligence?

AI has been long present in computer science with the general goal of creating "intelligent" machines (Holzinger et al., 2023), but intelligence is not specifically defined and even the assessment of "intelligence" is highly problematic (Holzinger et al., 2019). The AI movement commenced in 1956 when computer researchers gathered at Dartmouth College. It laid ambitious goals:

> "*The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves*", according to McCarthy and colleague cited in Holzinger et al. (2023).

AI, machine learning, and deep learning all fall under the same family but have unique characteristics. Some of the significant differences among these areas include:

- **AI** is a broad phrase and a vast research area with the aim of developing computerized systems with the capabilities of executing tasks involving intelligence, such as problem-solving, learning, and decision-making.
- **ML** is a subfield of AI that involves training digital computers to perform tasks without explicit instructions, using patterns and insights from data.
- **DL** is an ML branch using artificial networks with multiple layers for training as well as decision-making. It is utilized specifically in the processing of large amounts of data, such as images (e.g., DALL-E2) or text (e.g., ChatGPT).

Symbolic AI is a paradigm of AI through the use of symbolic representations of knowledge (Example: dog (*is-a mammal*) (*has-property fur*) (*has-property four-legs*)) as well as the use of logic-based rules in processing the symbols in problem-solving. It is distinct from machine learning as well as deep learning, which have no explicit rules but learn through the recognition of patterns in the data. Symbolic AI is no longer as widely applied as machine learning as well as deep learning have become more prominent in image as well as voice recognition. Nevertheless, symbolic AI is applied in certain fields, such as natural language processing as well as expert systems (Muggleton et al., 2018).

AI has been a highly broad field since its inception, from the philosophic reflections through the tangible applied work in the world (Russell & Norvig, 2020). More than any other area, AI has witnessed multiple boom-and-bust cycles since its official inception as a scholarly area sixty years ago. After expectations much too—"*within 10 years, whatever humans can do, a machine can do*" —the early excitement ended with a bitterly cold AI winter in the 1980s (Holzinger et al., 2023). The disillusioned sector, as well as multiple scientists, turned away from AI at the time—and even the acronym AI came close to being banned for a spell.

The astonishing breakthrough with statistical data-based ML again attracted attention to AI. Two factors have been and remain the reason for its applied success:

- Increasingly available data sets
- Increasingly available computational power

It was around 2010 when the ML-algorithm family DL turned out to be highly successful in the enterprise world as well as in daily life (Siri, Alexa, DeepL, etc.). This created a second AI spring—the best proof for the capabilities of AI these days is the newest natural language tool developed at OpenAI, ChatGPT (King, 2022), which demonstrates what AI can do (and cannot do, because lacking is still the human *Hausverstand*). The grand vision of AI is to provide the theoretical underpinning for ML in constructing computer programs with

the ability to learn from experience autonomously, automatically, with no human-in-the-loop (Shahriari et al., 2016). Lastly, in achieving the level of usable intelligence, we have to:

- Learn from experience
- Derive knowledge
- Generalize
- Counter the curse of dimensionality
- Separate the inherent explaining factors of the data

Machine learning is all about gaining insights regarding intelligence with the aim of constructing programs with the ability to learn from experience through the use of data, derive knowledge from experience, and improve their behavior regarding how they can keep improving. The issue is finding relevant structure and/or temporally relevant ("knowledge") patterns in the data, usually dormant in arbitrarily high-dimensional spaces and thus inaccessible to humans (Holzinger, 2019).

One grand issue remains: how to make the data meaningful in the context of the area of use. Good quality data and the optimal set of features matter the most, and earlier work showed the optimal-performing solutions tend to use combinations of multiple low-level features with higher-level context. But the optimal leverage of all AI/ML success is limited by the inability of the algorithm to reproduce the results, to understand and communicate its results to the relevant humans (Müller et al., 2022). It is a large issue in the life sciences as a whole, but also in biotechnology. Whether the rapid growth and spread of AI is a blessing or a curse, the fact is AI is going to penetrate, drive, and change virtually all areas of biotechnology in the future.

3. Evolution of Biotechnology with AI

The integration of artificial intelligence (AI) in biotechnology is changing the field of public health through more effective and low-cost solutions. A notable area in which AI is leaving a significant impact is drug discovery and drug development. Fleming (2018) and Aal et al. (2024) argue that machine learning (ML) is changing the process through the use of large databases of bioactivities of chemicals with the aim of being able to predict drug interaction more effectively. Additionally, breakthroughs in molecular biology have improved the understanding of the physiology of humans, with the discovery of flawed molecular forms as drug targets as well as the streamlining of drug discovery. In the past, drug discovery largely relied on guesswork, thereby being ineffective as well as a waste of time (Fleming, 2018; Aal et al., 2024; Swinney, 2024).

The pursuit of effective treatments and disease management strategies has always been a priority in public health. Before the advent of modern biotechnological approaches, humans relied on naturally occurring substances to mitigate illnesses (Gomes et al., 2024). A well-known example is aspirin, a drug whose active compound, salicylic acid, has been used for over 3,500 years. However, it took more than a century from the first extraction of salicylic acid from willow bark to the synthesis of aspirin in 1897. The process involved multiple chemical reactions in a trial-and-error approach to produce a stable and effective formulation (Montinari et al., 2019). Similarly, other widely used drugs, such as heparin and warfarin, underwent prolonged periods of discovery and characterization before their mechanisms were fully understood (Gomes et al., 2024).

AI is not just essential in laboratory experiments and data analysis but also indispensable in streamlining the vast literature review process underpinning every research study. Prior to the digital era, researchers depended upon books, hard copies of journals, institutional libraries, as well as scholarly collaboration to collect information—a tiresome and time-consuming process (Muthmainnah et al., 2022). The introduction of the internet facilitated the retrieval of scientific literature through digital libraries, online databases, as well as scholarly networks. Nonetheless, AI has advanced the process even more through automated screening of articles, summarization, translation, text analysis, as well as mining of data. AI-based resources like Connected Papers, SciSummary, ChatPDF, as well as Perplexity support researchers through the organization as well as

the synthesis of large volumes of scientific literature, facilitating the retrieval of information more effectively (Gomes et al., 2024).

Data analysis and imaging techniques have existed for decades, but prior to AI, these processes required significant manual effort and lacked efficiency. The integration of AI has dramatically improved data processing capabilities, allowing researchers to analyze and compare extensive datasets with greater precision and speed. By enhancing the accuracy and efficiency of biotechnological applications, AI is accelerating advancements in public health solutions. As explored in this discussion, AI is playing a transformative role in biotechnology, paving the way for sustainable public health innovations (Gomes et al., 2024). The subsequent sections will further elaborate on AI's contributions to various branches of biotechnology and their implications for public health.

4. AI and Biotechnology

The integration of biotechnology and artificial intelligence (AI) is paving the way for groundbreaking advancements in sustainable public health solutions. By combining AI with biotechnological approaches, researchers are now better equipped to analyze complex biological systems, leading to improved disease prevention, diagnosis, and treatment strategies. One of the most significant areas impacted by this convergence is genomics (Mudunuri et al., 2024). Utilizing AI techniques such as machine learning and deep learning, genomics research can now efficiently analyze vast amounts of genetic data, revealing intricate patterns and correlations in DNA sequences (see Table 1). This enhanced understanding of gene interactions and their role in various traits and diseases accelerates the development of personalized therapies and targeted treatments, ultimately contributing to more effective public health interventions (Abdullah, 2024).

Drug discovery is another area where the synergy between AI and biotechnology is driving significant advancements. AI systems are capable of rapidly analyzing extensive chemical and biological databases with greater speed and accuracy than traditional human-driven methods. This capability not only reduces the time and cost associated with drug development but also increases the likelihood of identifying effective treatments for a wide range of diseases (Suriyaamporn et al., 2024). Such efficiencies are critical for public health, as they enable quicker responses to emerging health threats and more accessible treatment options for underserved populations.

Table 1: AI-powered tools and techniques that enhanced biotechnological methods

SN	Machine Learning	Function	Application in Biotechnology	Reference
1.	XGBoost	Efficient Prediction	Drug Discovery and Development	Madanan et al., (2021)
2.	Random Forest	Pattern Recognition	Drug Discovery and Development	Cano et al., (2017)
3.	Artificial Neural Network	Precise Diagnoses	Personalized Medicine	Awwalu et al., (2015)
4.	SignatraX	Drug Target Identification	Transcriptomic	Jiang et al., (2005)
5.	CRISPR-P	Design High fidelity guide RNAs	CRISPR Technology	Liu et al., (2023)
6.	Generative Deep Neural Networks [GDNN]	Molecule Design	Drug Design	Dabdoub et al., (2022)
7.	Alpha Fold	Protein Structure Prediction	Drug Discovery and Development	Jumper et al., (2021)
8.	Deep Chem	Molecular Property Prediction	Drug Design	Korshunova et al., (2021)

9.	Soft Sensors	Estimate Bioprocess Parameters	Bioprocessing	Reyes et al., (2022)
10.	Deep Variant	Genomic Variation Analysis	Genomics	Supernat et al., (2018)
11.	Convolutional Neural Networks [CNN]	Protein Structure Prediction	Proteomics	Wen et al., (2020)
12.	DeepCpfR	Predicting off-target effects of guide RNA sequences	CRISPR Technology	Listgarten et al., (2018)
13.	Docking Simulations	Computer-aided Drug Discovery	Bio-molecular Engineering	Kore et al., (2012)
14.	Lifecycle Analysis	Assess the Environmental Impacts	Bioplastics	Ali et al., (2023)

Source: Adapted from Ali et al. (2024).

Moreover, the combination of AI and biotechnology has revolutionized synthetic biology, empowering researchers to engineer novel biological systems tailored for specific tasks. By predicting the functional outcomes of DNA modifications, AI significantly enhances the design and optimization of synthetic organisms or components (Muzamal et al., 2024). This capability facilitates the development of innovative solutions such as biofuels, biodegradable materials, and advanced drug delivery systems that are not only more efficient but also environmentally sustainable, aligning with public health goals of reducing pollution and improving overall health outcomes. Beyond these applications, the integration of AI and biotechnology is transforming various other fields with direct implications for public health, including ecology, energy, agriculture, and environmental sustainability. AI's ability to interpret complex biological data enables scientists to identify and address critical global health challenges, leading to innovative public health solutions (Holzinger et al., 2022; Holzinger et al., 2023; Liang et al., 2024; Rujano et al., 2024; Ali et al., 2024).

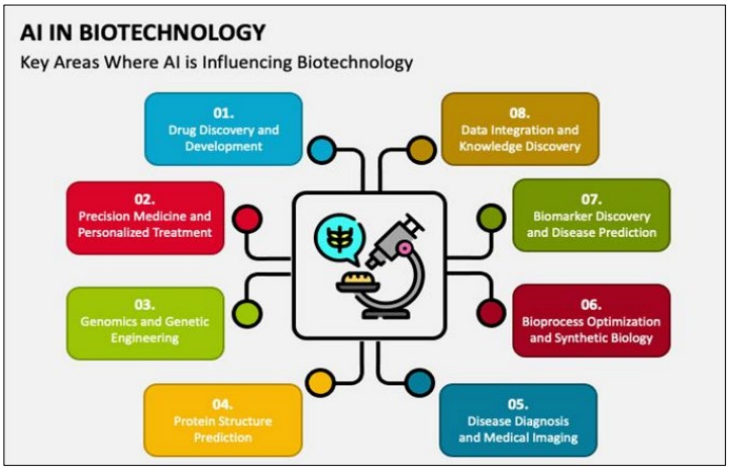


Figure 1: AI Influencing biotechnology

4.1. AI in Medical Biotechnology

The integration of AI in medical biotechnology presents vast potential to improve sustainable public health by enabling faster, more accurate, and cost-effective discovery and development of medical interventions. AI significantly contributes to improving healthcare accessibility and outcomes. Some of the key areas where AI is transforming medical biotechnology include:

AI and Infectious Disease Vaccine Discovery

AI and machine learning (ML) are revolutionizing vaccine discovery, particularly for infectious diseases, by enhancing predictive accuracy and speeding up candidate identification. One transformative approach is reverse vaccinology, which uses bioinformatics to analyze genomics and proteomics interactions between

pathogens and hosts (Patil and Shreffler, 2019). This method was first successfully applied in the development of the Meningitis B vaccine, paving the way for vaccines targeting Streptococcus (Prevnar 13), Herpes Zoster (Shingrix), and Malaria (Mosquirix) (Hare et al., 2024; Lal et al., 2015). More recently, AI-driven reverse vaccinology has accelerated vaccine research for emerging public health threats, including COVID-19 (Bai et al., 2024; Hare et al., 2021b; Ishack and Lipner, 2021; Malone et al., 2020), HIV (Gaiha et al., 2019; McGowan et al., 2021), Hepatitis (Ikram et al., 2023), Shigella (Aiman et al., 2023), and antimicrobial resistance (AMR) (Khalid and Poh, 2023).

AI models optimize vaccine designs by predicting a broad range of CD8 and CD4 T-cell epitopes, ensuring population-wide immunogenic coverage (Ong et al., 2020; Reynisson et al., 2020; Hare et al., 2021a; Mazzocco et al., 2021). Complementing cellular immunity, AI tools are also enhancing humoral responses by facilitating the design of functional neutralizing antibodies. For instance, Magar et al. (2021) employed machine learning to identify eight antibodies with potential neutralization effects against SARS-CoV-2, utilizing a dataset (VirusNet) comprising antigen-antibody interactions from various viral diseases, including HIV, influenza, and Ebola. Similarly, AI/ML approaches are being used to redesign the variable loops of the HIV-1 envelope to stimulate broadly neutralizing antibodies (Bai et al., 2024). These innovative AI applications enhance vaccine efficacy and adaptability, thus supporting sustainable public health by enabling rapid responses to emerging infectious threats.

AI is also pioneering proactive vaccine development by predicting the evolution of pathogens. EVEscape, developed by Thadani et al. (2023), is a modular AI framework that combines deep learning with biophysical and structural data to forecast pathogen variant evolution. This anticipatory approach supports the design of vaccines for future variants, thereby enhancing public health preparedness. The potential of AI/ML extends beyond discovery, influencing all stages of the vaccine development pipeline to optimize efficacy, safety, and cost-effectiveness, thereby contributing to sustainable public health solutions.

AI and Vaccine Development Lifecycle

The traditional vaccine development lifecycle, from discovery to regulatory approval, typically spans 8–12 years (BMG LABTECH, 2020). However, AI/ML integration has the potential to significantly accelerate this timeline, as demonstrated by the expedited development of COVID-19 vaccines within 10 months (Rahman et al., 2022; Saag, 2022; Saag, 2023). This acceleration was facilitated by AI's ability to analyze massive datasets, optimize candidate selection, and enhance preclinical and clinical trial designs, thus reducing both time and costs. Sustainable public health relies on the ability to rapidly respond to emerging health threats with safe and effective vaccines. AI's predictive models enhance target selection and preclinical testing accuracy, thereby increasing the likelihood of clinical success and reducing the risk of failure due to lack of efficacy (Plenge, 2016; Herati & Wherry, 2018; Vijayan et al., 2022). By creating a feedback loop between discovery research and early clinical data, AI enables an integrated development paradigm that allows continuous optimization of vaccine candidates (Figure 2a&b). This iterative approach enhances vaccine efficacy, safety, and scalability, ensuring sustainable public health outcomes by enabling faster access to life-saving immunizations.

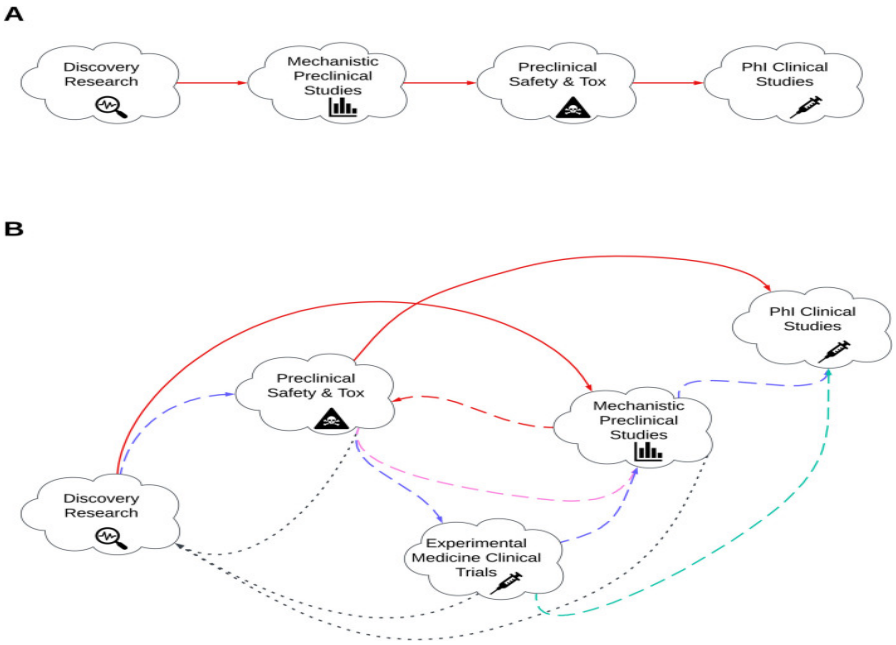


Figure 2a&b: Illustration of the early phases of vaccine development. (A) traditional linear paradigm of vaccine development. (B) Reimagined vaccine development pathway. Red lines represent existing development pathway. Alternative coloured lines represent more dynamic pathway whereby by products move between clinical and clinical research phases. Blue, purple, turquoise and black represent the alternative development routes based on previous phase outcomes. Dashed lines indicate activities that progress in alignment to traditional model. Dotted lines indicate more iterative activities.

AI and Drug Discovery and Development

AI is revolutionizing drug discovery and development, thereby enhancing public health by increasing the speed, cost-effectiveness, and precision of therapeutic interventions. The pharmaceutical industry faces challenges of high costs and long development timelines, often exceeding a decade. AI addresses these challenges by rapidly identifying hit and lead compounds, optimizing drug design, and improving target validation (Mishra, 2018; Sellwood et al., 2018; Paul et al., 2021). This efficiency not only accelerates drug development but also lowers costs, making essential medicines more accessible, particularly in low-resource settings. AI tools (see figure 3) are utilized at various stages of drug discovery, including virtual screening for identifying promising drug candidates from extensive molecular databases (Ali et al., 2024) and toxicity prediction for assessing safety risks (Ali et al., 2024). Machine learning algorithms like XGBoost (Madanan et al., 2021) and Random Forest (Cano et al., 2017) are instrumental in predicting drug efficacy and safety profiles. Additionally, deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative deep neural networks (GDNNs), are widely used for complex tasks such as protein structural modeling (Gao et al., 2020; Dabdoub et al., 2022) and high-dimensional genomic data analysis. These tools enable the design and simulation of drug molecules that precisely target disease mechanisms, leading to more effective and personalized treatments. Prominent AI applications in drug discovery include AlphaFold for protein structure prediction (Jumper et al., 2021) and DeepChem for molecular property prediction and drug design (Korshunova et al., 2021). By enabling accurate predictions of drug-target interactions and accelerating preclinical testing, these AI tools reduce development time and costs. This efficiency not only enhances pharmaceutical innovation but also supports sustainable public health by ensuring rapid availability of safe and effective treatments for emerging diseases.

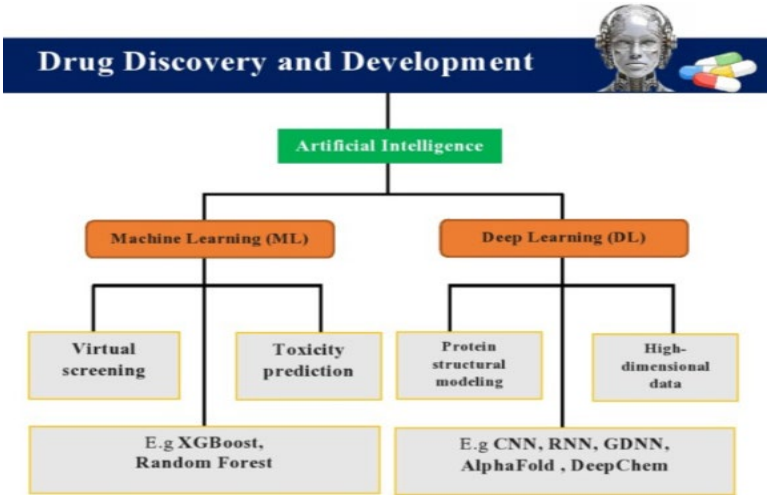


Figure 3: AI-powered tools and techniques in drug discovery and development

5. A Synergistic Approach to Sustainable Public Health Solutions Using Biotechnology and Artificial Intelligence

Hadley et al. (2020) propose a conceptual framework to guide the development of sustainable public health solutions through the integration of biotechnology and artificial intelligence (AI). This approach emphasizes four key components: (1) Public Health Intervention, (2) AI and Biotechnology Integration, (3) Resource Sustainability, and (4) Synergistic Program Design (see figure 4). The first component, Public Health Intervention, involves identifying the specific healthcare challenge to be addressed. This sets the stage for selecting the most suitable AI model and biotechnological approach to optimize the intervention. For instance (figure 4), intelligent electronic records can enhance data management (Lu et al., 2017), while biosurveillance systems can monitor and predict disease outbreaks (Nguyen & Nguyen, 2015; Natsiavas et al., 2016; Hadley et al., 2020). Diagnostic tools powered by AI can facilitate early detection and personalized treatment plans (Ting et al., 2017; Umoh et al., 2015), and clinical decision support systems can assist healthcare professionals in making accurate diagnoses and treatment decisions (Esteva et al., 2017). Additionally, automated planning and scheduling can optimize resource allocation in healthcare settings (Hadley et al., 2020).

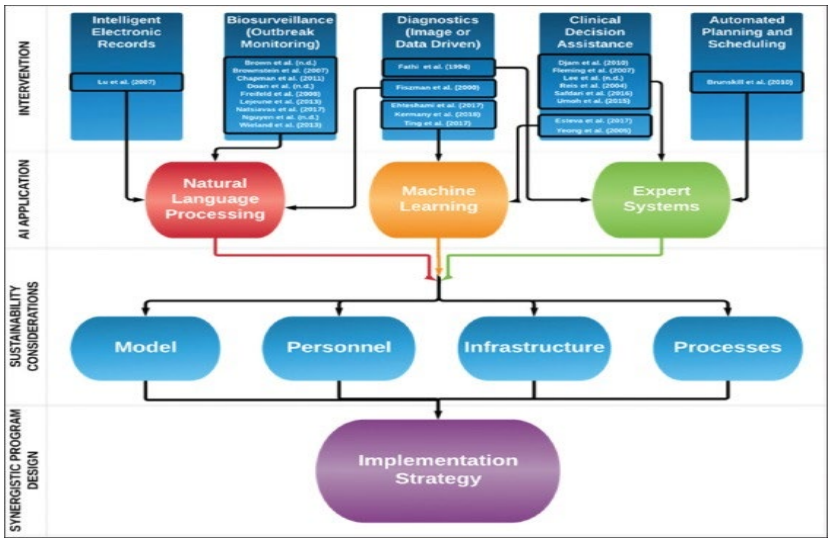


Figure 4: A process for development of an artificial intelligence driven health initiative. (Adapted from Hadley et al. 2020).

The second component, AI and Biotechnology Integration, involves selecting the appropriate AI model that complements the biotechnological solution to address the identified public health issue. This choice should be tailored to optimize model performance while ensuring scalability and adaptability to local contexts. Following

model selection, it is crucial to assess sustainability considerations. This involves evaluating resource demands such as maintenance, personnel training, and infrastructure needs, ensuring that the chosen solution remains functional and effective over the long term.

The third component, Resource Sustainability, emphasizes the need for a resource-conscious strategy that enables the transition from a predominantly vertical, top-down program to one that is more horizontally integrated and self-sustaining. This involves considering four key resource categories: (1) Model Development and Maintenance, (2) Skilled Personnel, (3) Infrastructure, and (4) Process Optimization. Ensuring resource sustainability necessitates proactive planning, particularly in resource-limited settings, to facilitate long-term viability and impact (see figure 5).

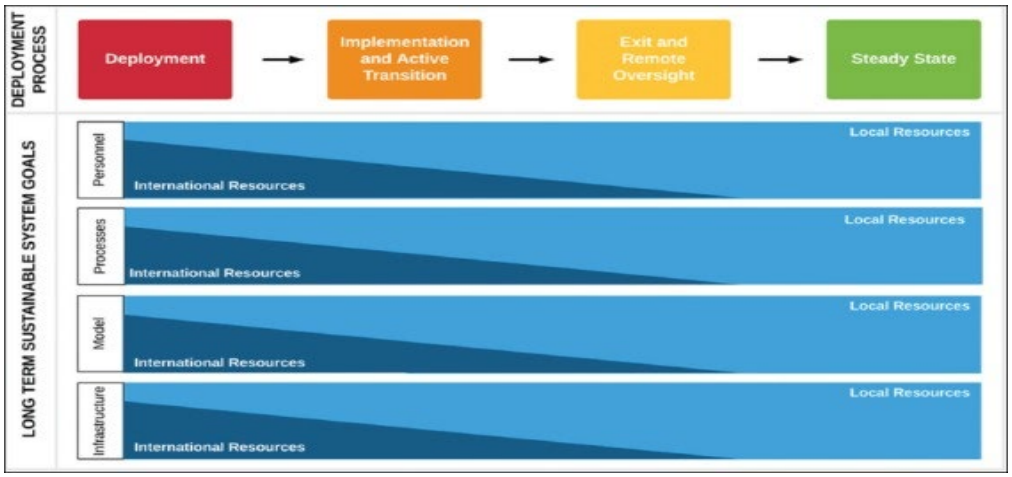


Figure 5: A potential strategy for implementation of a synergistic AI driven health initiative. (Adapted from Hadley et al. 2020).

The fourth component, Synergistic Program Design, focuses on designing programs that are context-specific and adaptable to resource-constrained environments. This involves developing a pre-implementation strategy that accounts for the specific resource requirements of the chosen AI-biotechnology application. Such strategic planning is essential to optimize resource allocation and ensure sustainable deployment.

To achieve sustainable public health solutions, it is crucial to establish a self-sustaining model in the target region. Initially, international support may be required for the deployment of AI systems, including model development, infrastructure setup, and personnel training. However, a strategic transition plan should be in place from the onset to progressively localize these resources. This includes training local healthcare providers and building local technical capacity, ensuring that the system becomes increasingly independent of external support.

As the AI and biotechnology integration becomes fully operational, the program should aim to transition personnel and operational processes to local stakeholders. This requires comprehensive training programs and knowledge transfer initiatives to empower local communities. In some regions, infrastructure constraints may delay the complete transition to local resources. Nonetheless, achieving a steady-state system—where local infrastructure supports the personnel needed to maintain the model and operational processes with minimal external assistance—remains the ultimate goal. This localized sustainability is crucial for creating durable public health solutions that are resilient and adaptable to evolving health challenges (Hadley et al., 2020).

6. Challenges and Limitations of Using AI in Sustainable Public Health Solutions

Although AI holds immense potential for advancing sustainable public health through biotechnology, several challenges and limitations hinder its widespread adoption and African health sector are not left out of these barriers as outlined in Table 2. While AI can improve accessibility and efficiency in healthcare, it can also

exacerbate existing disparities if not implemented responsibly. AI models heavily depend on the quality and diversity of the datasets used for training. Consequently, biases in these datasets can lead to inequitable outcomes, particularly for underrepresented groups.

Table 2: Barriers to AI integration in the African health sector

Barriers	African Countries	Reference
Infrastructure and technology challenges		
Low internet penetration and limited access to high-performance computers	Uganda and Kenya	Owoyemi et al. (2020)
Prohibitive cost of high-performance computers	Nigeria	Takuwa et al. (2023)
Lack of clear policies for e-health development	Kenya	Owoyemi et al. (2020)
Data privacy and security concerns		
Concerns about patient information handling	Kenya	Mbuthia et al. (2019)
Health database reach	South Africa	Neto et al. (2021)
Healthcare workforce and training acceptance		
Lack of confidence, knowledge and skills in using ICTs	Ghana and Uganda	Yagos et al. (2017), Johnson (2018) and Peprah et al. (2019)

Source: Adapted from Oladipo, Adeyemo, Oluwasanya, Oyinloye et al. (2024).

Data Bias and Algorithmic Fairness: AI systems are only as reliable as the data they are trained on. In public health, biased or incomplete datasets can lead to inaccurate predictions and discriminatory outcomes. This is particularly concerning when using AI for disease diagnosis, treatment recommendations, or public health surveillance, as these systems may amplify health disparities. For example, underrepresentation of certain demographic groups in training datasets can result in AI models that perform poorly for these populations, thus widening health inequities. Ensuring algorithmic fairness requires comprehensive and diverse data collection, robust metadata management, and rigorous model evaluation to identify and correct biases (Liong-Rung et al., 2022; Popovic et al., 2024). Additionally, the complexity of neural networks poses challenges for transparency and accountability. Since deep learning models are often considered "black boxes," understanding their decision-making processes is difficult. This lack of interpretability undermines trust among healthcare providers and patients, which is crucial for sustainable public health integration. To address this, AI models should be developed and evaluated under the guidance of domain experts who can ensure accuracy and fairness in real-world applications.

Data Accessibility and Privacy Concerns: Access to high-quality clinical and health data remains a significant barrier to adopting AI in public health. Organizational policies, legal restrictions, and privacy concerns often limit data sharing, hindering the development of robust and generalizable AI models. In healthcare, data fragmentation and siloed information systems impede seamless data integration, leading to inconsistencies in outcome assessments and model reproducibility. This challenge is particularly relevant for sustainable public health, where accurate, real-time data is crucial for monitoring disease outbreaks, evaluating intervention efficacy, and guiding policy decisions (Mbuthia et al., 2019; Park et al., 2020; Winter, 2021; Kumar & Joshi, 2022; Kuzlu et al., 2023; Mennella et al., 2024). Data privacy and security are fundamental concerns in AI-driven public health solutions. Patients and communities are often unaware of how their data is collected, stored, and used, raising ethical issues related to consent and data ownership. Ensuring data privacy while maintaining utility for public health analysis requires advanced anonymization techniques and transparent data governance policies. To build trust and encourage data sharing, it is essential to clearly communicate the benefits of AI integration for public health and ensure data usage aligns with ethical standards.

Model Accuracy and Clinical Validation: One of the significant limitations of AI in public health is the inconsistency in model accuracy and clinical validity. AI algorithms, particularly in medical diagnostics, have

shown varying performance across different demographic groups due to biased training datasets. For instance, an AI model developed to detect pneumothorax from chest X-rays mistakenly identified chest tubes as pneumothorax, highlighting the risks of false positives and misdiagnoses (Liong-Rung et al., 2022; Popovic et al., 2024). Such inaccuracies compromise patient safety and public trust, posing significant challenges for sustainable public health integration. Additionally, AI models require rigorous clinical validation before deployment in healthcare settings. This involves testing model performance across diverse populations and environments to ensure robustness and generalizability. However, the lack of standardized evaluation protocols and insufficient reproducibility in dataset processing remain major obstacles. Collaborations between AI developers, healthcare professionals, and regulatory bodies are crucial to establishing standardized validation frameworks that ensure clinical efficacy and safety.

Computational Resources and Infrastructure Limitations: AI models, especially deep learning networks, require substantial computational power and resources for training and deployment. In public health settings, particularly in low-resource regions, limited access to advanced computing infrastructure poses a significant barrier. Additionally, the computational time required for processing large datasets can vary widely, impacting the efficiency of real-time public health monitoring and decision-making. However, some researchers are trying to assess biases by testing how well the algorithms predict outcomes when they randomly change key variables for individuals. The lack of adequate ICT infrastructure, including low internet penetration rates and limited access to high-performance computers, makes it difficult for healthcare systems to adopt and implement AI systems. The cost of purchasing, maintaining and upgrading high-performance computers is often prohibitively expensive for healthcare systems that rely on funding (Wahl et al., 2018; Dodoo et al., 2021; Onsongo et al., 2023; Mbunge & Batani, 2023). To address these challenges, scalable and resource-efficient AI models are needed. Cloud-based solutions and federated learning approaches offer potential for decentralized data processing while maintaining data privacy. Moreover, optimizing AI algorithms to run on low-cost hardware can enhance accessibility and sustainability, especially in underserved communities.

Ethical and Regulatory Challenges: Ethical considerations are crucial when implementing AI in public health, particularly regarding patient autonomy, informed consent, and data transparency. In public health surveillance, the use of AI for predictive analytics raises questions about the ethical implications of tracking individuals or populations (Oladipo et al., 2024). Additionally, biases in AI models can lead to discriminatory public health policies or interventions, exacerbating health disparities. Regulatory challenges further complicate AI integration into public health systems. Currently, there is no unified regulatory framework for evaluating AI tools in healthcare, leading to inconsistencies in safety and efficacy standards. Establishing clear guidelines for ethical AI usage, including accountability mechanisms for decision-making, is essential for ensuring public trust and equitable health outcomes.

Resource Constraints and Cost Implications: The financial costs associated with developing and deploying AI systems can be prohibitive, particularly for public health organizations operating under budget constraints. For example, high-resolution imaging technologies used in AI-powered disease surveillance or diagnostics are often expensive and inaccessible to low-resource healthcare systems. In agricultural biotechnology, a sector closely linked to public health through food security and nutrition, AI-based drone technologies require costly equipment and regulatory authorization, limiting their adoption by small-scale farmers (Oladipo et al., 2024). To enhance sustainability, cost-effective AI solutions tailored to the needs of resource-limited public health systems are needed. Open-source AI platforms and public-private partnerships can help reduce costs and promote technology transfer to underserved regions. Additionally, capacity-building initiatives should focus on training local public health professionals in AI deployment and maintenance, fostering self-reliance and long-term sustainability.

Interdisciplinary Collaboration and Skill Gaps: Successful integration of AI in public health requires interdisciplinary collaboration among data scientists, healthcare professionals, biotechnologists, and policymakers. However, a lack of relevant skills and expertise in both AI and public health domains poses a significant challenge (Oladipo et al., 2024). Bridging this gap requires comprehensive training programs that equip public health practitioners with AI literacy while enabling data scientists to understand healthcare contexts. Promoting interdisciplinary research and establishing collaborative networks can accelerate AI innovation for sustainable public health. Additionally, fostering public-private partnerships can enhance knowledge sharing and resource pooling, driving sustainable AI deployment in public health systems worldwide.

7. Opportunities for Sustainable Public Health Solutions through Biotechnology and AI

The integration of biotechnology and AI presents numerous opportunities for advancing sustainable public health solutions (see figure 4), particularly in emerging economies (Lee & Yoon, 2021). According to Muzamal et al. (2024), in order for the Biotechnology-AI Nexus to realize its full potential, we must overcome its challenges, among these is the requirements for interdisciplinary collaboration, concerns about data security and privacy, moral conundrums, regulatory compliance, and others. Also, to allay these worries, scientists, medical professionals, policymakers, and business representatives should work together to create an atmosphere that encourages responsible innovation and guarantees a fair distribution of the benefits (Ahmed et al., 2017). This section explores six key areas where these technologies can drive impactful change.

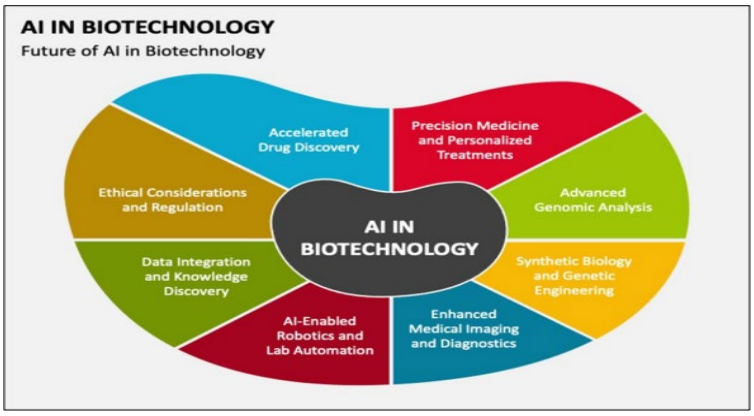


Figure 4: Future of ai in biotechnology

Building Local Expertise in Digital Health Technologies

Emerging economies hold untapped potential in digital health technologies, yet their expertise is often underrecognized on the global stage. Researchers and engineers from these regions have made significant strides in bioinformatics, computational biology, and automation, contributing to innovative solutions in healthcare (Moreno et al., 2022; Denecke & Baudoin, 2022). For instance, India's launch of Aptio Automation in 2017 marked a milestone in laboratory automation, demonstrating the power of local multidisciplinary collaboration in healthcare innovation (da Silva, 2024). This project united expertise across science, engineering, and manufacturing, setting a foundation for scalable autonomous systems in public health diagnostics. Similarly, Brazil's integration of automation systems within a mega-volume clinical laboratory showcased the potential of interconnected healthcare platforms (da Silva, 2024). These examples illustrate how regional competencies can be harnessed to enhance AI-driven healthcare solutions and promote sustainable public health systems. To fully leverage these innovations, international collaboration and knowledge exchange are crucial. By partnering with global health technology developers, emerging economies can contribute to robust AI models tailored to local public health needs, enhancing data robustness and enabling more effective public health interventions (Graña et al., 2016).

Digital Collaboration to Overcome Healthcare Disparities

Emerging economies face significant disparities in scientific and technological capabilities compared to high-income countries, impacting their public health infrastructure (Mazzucato, 2018). Decentralized digital platforms, powered by AI, can bridge this gap by facilitating collaborative research and knowledge sharing. In Southeast Asia, initiatives such as the Asian Consortium of Computational Materials Sciences (ACCMS) have demonstrated the potential of regional collaborations to advance digital health and AI research (Kroll & Frietsch, 2022). Similarly, Singapore's Advanced Remanufacturing and Technology Centre (ARTC) serves as a hub for public-private partnerships in digital health, enhancing regional research capacity (Wong, 2022; A*STAR, 2023). Cross-regional collaborations, like those facilitated by the Vector Institute in Canada and the Programa Iberoamericano de Ciencia y Tecnología in Latin America, emphasize the strategic importance of global knowledge exchange to strengthen AI applications in public health (da Silva, 2024). These initiatives enable emerging economies to access advanced AI tools and methodologies, enhancing their capability to tackle local public health challenges.

AI-Driven Solutions for Global Health Challenges

Current drug discovery systems and public health interventions often fail to address persistent health challenges in low- and middle-income countries (Ingber, 2022; Reidpath & Allotey, 2019). AI offers transformative potential by accelerating clinical innovations tailored to the unique health needs of emerging economies. For example, AI can revolutionize vaccine development and molecular diagnostics, particularly for neglected tropical diseases and re-emerging epidemics (Anderson, 2021). Countries like India, Brazil, and Indonesia possess deep knowledge of infectious diseases, which, when combined with AI-driven biotechnology, can lead to effective public health solutions tailored to local contexts. Moreover, decentralized AI collaborations can enhance global health responses to emergencies, as demonstrated during the Covid-19 pandemic, highlighting the need for resilient and context-specific public health strategies (Leach et al., 2021; McNamara et al., 2020). By leveraging local expertise and integrating AI with biotechnology, emerging economies can contribute to a more equitable global health landscape.

Advancing Science and Innovation Diplomacy

Science and Innovation Diplomacy (S&ID) is crucial for fostering international collaboration in public health technology. Emerging economies can leverage S&ID to participate in global health networks, influencing policy decisions and ensuring equitable access to AI-driven public health innovations (Torres & Riordan, 2023). For example, international organizations like the Pan American Health Organization (PAHO) and the Global Alliance for Vaccine and Immunization (GAVI) have used S&ID frameworks to promote collaborative health solutions tailored to the needs of emerging economies (da Silva, 2024). By actively engaging in S&ID initiatives, these countries can shape global health policies and drive sustainable public health innovation. However, effective S&ID requires strategic alignment between scientific priorities and foreign policy goals. Collaborative platforms should focus on building capacity and facilitating dialogue between policymakers, scientists, and healthcare practitioners, ensuring that AI-driven public health solutions are inclusive and contextually relevant.

Co-creating Ethical and Regulatory Frameworks

The integration of AI and biotechnology in public health raises ethical and regulatory challenges, especially concerning data privacy, accountability, and equitable access. Emerging economies have the opportunity to co-create ethical frameworks that reflect diverse cultural and societal values, ensuring responsible AI deployment in healthcare. Collaborations between policymakers, scientists, and civil society organizations can lead to inclusive regulatory standards, fostering public trust and social acceptance of AI technologies in public health (Gwagwa et al., 2019; Alami et al., 2020). Furthermore, international partnerships can provide the necessary empirical evidence to establish effective ethical guidelines, supporting the responsible integration of AI in biotechnology for public health (King et al., 2018; Maffettone et al., 2023).

Promoting Diversity, Equity, Inclusion, and Trustworthiness (DEIT)

Diversity, equity, inclusion, and trustworthiness (DEIT) are fundamental to the ethical deployment of AI in public health. By actively involving researchers from emerging economies, AI solutions can be tailored to diverse public health contexts, leading to more comprehensive and inclusive healthcare innovations (Reardon et al., 2023). To achieve this, global research initiatives should prioritize capacity-building, technology transfer, and equitable funding mechanisms, empowering local stakeholders to develop AI-driven solutions for their communities. Moreover, fostering transparency and accountability through collaborative governance structures will enhance public trust and support the sustainable adoption of AI technologies in public health (Zhang, 2017; Takashima et al., 2021).

8. Conclusion

The integration of biotechnology and artificial intelligence (AI) presents a groundbreaking opportunity to address persistent public health challenges sustainably. By enhancing drug discovery, vaccine development, and disease management, these technologies can significantly improve health outcomes and accessibility. As we have explored, AI's capacity to analyze vast datasets and identify patterns accelerates the pace of innovation, leading to more effective health interventions tailored to diverse populations. However, the journey toward sustainable public health solutions is fraught with challenges, including data bias, algorithmic fairness, and ethical concerns surrounding privacy and consent. It is imperative that we prioritize interdisciplinary collaboration to bridge the gap between AI technology and public health practices. This collaboration should involve stakeholders across various sectors, ensuring that innovations are culturally sensitive and contextually relevant. Moreover, fostering local expertise in emerging economies will be crucial in harnessing AI's potential for tailored public health solutions. Investments in education and infrastructure will empower communities to develop and implement these technologies effectively. By establishing ethical frameworks and promoting diversity, equity, and inclusion in AI applications, we can work towards a future where health disparities are minimized, and sustainable public health solutions are accessible to all. Additionally, the integration of biotechnology and AI offers a promising pathway for revolutionizing public health. By addressing existing challenges and leveraging local knowledge and capabilities, we can create a resilient and equitable health system that meets the needs of diverse populations worldwide.

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