

# The Way Forward to Embrace Artificial Intelligence in Public Health

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The promise of revolutionizing disease surveillance, health service delivery, and medical research through the integration of artificial intelligence (AI) is real.<sup>1</sup> The capabilities of AI, from predictive analytics to automated decision-making, have been aptly explored in medical research and health care delivery in recent years, but the unparalleled opportunities to improve public health outcomes have yet to be harnessed to the same extent. AI-powered predictive analytics can be used to analyze large data sets, identify risk factors for disease, detect patterns, and predict outbreaks.<sup>2</sup> However, the path to realizing the full potential of AI in public health is fraught with challenges that must be carefully navigated.<sup>3</sup>

The impetus for exploring AI readiness in public health stems from the urgent need to address the escalating complexity of global health challenges.<sup>4</sup> Rising health care costs, the emergence of novel pathogens, and the growing prevalence of chronic diseases are pushing the boundaries of traditional public health strategies.<sup>5</sup> AI is poised to

augment human efforts by analyzing big data, identifying patterns, and predicting public health crises. However, realizing its potential will require overcoming key challenges in AI readiness, adoption by practitioners, and integration into public health systems.<sup>6</sup>

## KEY CHALLENGES FOR AI INTEGRATION

This article examines five key challenges impeding AI's integration in public health, despite its immense potential, and offers insights to overcome these barriers for effective implementation:

1. Improve transparency and applicability for professionals to enable trust and effective use of AI in health care;
2. Address data bias and quality issues to improve AI development and practical application;
3. Establish standardized protocols and dual-use controls to facilitate the use of AI in production;
4. Implement human-in-the-loop approaches to improve the accuracy and reliability of AI systems; and

5. Develop a robust AI infrastructure to ensure readiness for integration into public health practice.

This article synthesizes the evidence on AI in public health, highlights key challenges, and proposes a structured approach to address them. It advocates for interdisciplinary collaboration, high-quality data, dual-use controls, continuous human feedback, and investment in AI-enabled infrastructure. By addressing these critical issues, the article aims to catalyze transformative thinking and advance AI readiness in the vital field of public health.

## Challenge 1: Transparency and Acceptance

The opacity of AI techniques is a significant barrier to their integration into public health, fostering skepticism and unrealistic expectations among professionals. To overcome this challenge, it's critical to develop and implement clear guidelines that address ethical considerations, transparency, accountability, and interpretability.<sup>7</sup> These measures will ensure that AI systems provide transparent rationales for their decisions, thereby fostering trust and facilitating effective collaboration between AI and public health professionals.

The COVID-19 pandemic highlighted the transformative potential of AI in public health through effective virus tracking and hotspot prediction, and underscored the need for transparency and expert trust. These lessons might have helped inform the European Union's (EU) AI Act, which sets ethical guidelines for AI use. It emphasizes the importance of human oversight and responsible use.<sup>8</sup> In medical diagnosis, AI systems must not only make recommendations, but also provide transparent

and understandable explanations of their reasoning.<sup>9</sup> By integrating Explainable AI with interdisciplinary collaboration, we can foster trust among health care professionals and ensure responsible AI implementation. Prioritizing transparency, ethical standards, and interpretability will help overcome skepticism and enable AI to improve patient outcomes and health care efficiency.

## Challenge 2: Data Bias and Data Quality

When AI is applied to public health, data quality faces significant challenges, including regulatory restrictions, compatibility issues, and data gaps. These barriers impede the development and implementation of AI. In addition, privacy concerns and biases, such as underrepresentation of minorities, can compromise data reliability. Overcoming these barriers requires robust data-centric frameworks that facilitate the secure sharing of high-quality, unbiased data, which is essential for effective AI use in public health.<sup>10</sup>

Google DeepMind's collaboration with Moorfields Eye Hospital demonstrated the potential of AI to detect eye disease through anonymized scans, but it faced challenges with low-resolution images and lighting variations. This example highlights the critical importance of robust, data-centric frameworks for AI applications in public health. Such frameworks, such as the European Health Data Space, are essential for integrating diverse data sources—including electronic health records and social determinants of health—to create accurate predictive models and targeted interventions.<sup>11</sup> By prioritizing comprehensive data-centric approaches that address quality, bias, and integrity concerns, public health

institutions can foster an environment conducive to AI readiness and ensure that systems remain effective and equitable in real-world health care settings.<sup>12,13</sup>

## Challenge 3: Standards and Dual-Use Controls

The lack of standardized protocols for the dual use of AI in public health significantly hinders its seamless integration into health systems, despite AI's proven capabilities in data processing and analysis. Establishing such standards is critical to ensuring the effective use of AI for both public health and administrative functions, thereby unlocking its full potential in health care.

Integrating AI into health care diagnosis and treatment planning requires a comprehensive approach centered on the nested model for AI design and validation.<sup>14</sup> This model, along with standardized data formats and interoperability protocols,<sup>15</sup> aims to streamline the integration of AI into existing health care systems while maintaining dual-use capabilities for public health and administrative functions. The EU AI Act seeks to regulate these systems based on their potential impact, balancing innovation with necessary safeguards. However, challenges remain, as exemplified by AI-assisted mental health screening using social media and social network data. This underscores the urgent need for robust regulatory frameworks to protect privacy and mitigate bias, and highlights the delicate balance between technological advancement and ethical considerations in health care AI applications.<sup>16,17</sup>

## Challenge 4: Accuracy and Reliability

The integration of human-in-the-loop mechanisms is critical to improving the

accuracy and trustworthiness of AI applications in public health. Although AI excels at processing medical data, its generalizability remains limited. Continuous human feedback enables error identification and correction, refining AI-generated insights and improving the reliability of AI-driven recommendations.<sup>18</sup> This human-in-the-loop approach ensures that human expertise consistently validates and improves AI systems, ultimately leading to more trustworthy and accurate public health decisions.

In medical AI applications, continuous human feedback is critical for identifying and correcting inaccuracies or biases in AI-generated recommendations. This iterative process of human oversight and AI refinement enhances system reliability, mitigates errors, and builds trustworthiness, ultimately maximizing AI transparency and acceptance among health care professionals. A study has found that large language models in medical settings can produce inaccurate cancer treatment advice, underscoring the critical need for human expertise to validate AI recommendations.<sup>19</sup> This highlights the importance of proper training and resources for health care professionals to effectively collaborate with AI systems to ensure patient safety and optimal care.

## Challenge 5: Compatible Infrastructure

Integrating AI into public health requires an AI-enabled infrastructure for building, testing, training, and deploying applications. This requires significant investment in secure, scalable systems that can support AI while protecting personal data from breaches and unauthorized access. Prioritizing the development of robust infrastructure mitigates the risks associated with AI integration and fosters an

environment that protects privacy and maintains data integrity and security in public health systems.

The COVID-19 pandemic's use of AI in contact-tracing applications has illustrated both the potential and the challenges of AI in public health, particularly in terms of infrastructure, privacy, and security.<sup>20</sup> This experience underscores the need for a resilient and secure infrastructure capable of processing large amounts of data while adhering to strict privacy protocols. The development of these applications demonstrated the delicate balance required between leveraging AI for public health benefits and protecting individual privacy. By prioritizing investments in secure, scalable infrastructure and clear privacy policies, we can foster trust in AI-driven technologies while maintaining the high standards necessary for the responsible use of health data in an AI-enabled landscape.

## THE WAY FORWARD TO EMBRACE AI IN PUBLIC HEALTH

To successfully integrate AI into public health, a proactive and collaborative approach is essential to address

associated challenges and limitations. We propose a five-step validation board, outlined in [Box 1](#), to guide stakeholders through the process of fostering AI readiness in public health with transparency. This multifaceted approach, with each step highlighting two key points, aims to navigate the complexities of AI integration while maintaining integrity and effectiveness in public health applications. We also provide a hierarchical mind map for AI preparedness in public health (see Supplemental Figure A, available as a supplement to the online version of this article at <http://www.ajph.org>).

### Step 1: Promoting Transparency

The adoption of AI in public health requires transparency and comprehensibility for health care professionals and experts. This fosters trust, acceptance, and effective collaboration between AI developers and domain experts, leading to more impactful solutions. The objective of step 1 is to ensure that AI solutions are transparent and understandable to health care professionals and public health experts.

Explainable AI models are critical to fostering trust and understanding of AI decisions among health care professionals. Tjoa and Guan's study highlights how explainability increases the acceptability of AI in sensitive health applications,<sup>21</sup> as exemplified by DeepMind's Streams app for risk assessment of kidney injury, which prioritizes transparency through detailed information disclosure and independent review.<sup>22</sup> At the same time, Wilson and Daugherty's article highlights the importance of collaboration between AI developers and health care professionals, and how this synergy leads to more impactful, tailored AI solutions.<sup>23</sup> Mayo Clinic's AI for radiology illustrates this approach, providing extensive documentation and training for radiologists to foster collaborative intelligence and effective AI adoption.

### Step 2: Advocating for High-Quality, Unbiased Data

High-quality, unbiased data are the foundation for AI systems to make accurate predictions and equitably address public health challenges. The objective of step 2 is to highlight

## BOX 1— Validation Board to Help Stakeholders Navigate Through a Plan to Promote Artificial Intelligence (AI) Readiness in Public Health With Transparency

Steps	1. Promoting Transparency in AI Adoption	2. Advocating for High-Quality, Unbiased Data	3. Implementing Standards and Dual-Use Controls	4. Enhancing AI Reliability With Human Feedback	5. Building Robust Infrastructure for AI Model Training and Testing
1st key point	Health care professionals must try to understand how AI decisions are made to gain trust and acceptance.	Quality data are crucial for accurate predictions and equitable management of public health challenges.	Dual-use implications of AI require controls to limit misuse and ensure safe applications.	Human oversight ensures ethical, fair, and accountable decisions in AI applications.	Robust AI infrastructure is essential for effective implementation of AI solutions in public health.
2nd key point	Collaboration between AI developers and health experts enhances solution effectiveness.	Addressing data bias is essential to prevent skewed outcomes affecting specific populations.	Standards for dual-use controls prevent harmful uses and promote positive outcomes.	Integrating human expertise supports trust and reliability in AI-driven public health initiatives.	Adequate infrastructure includes technical components and organizational capacity.

the importance of unbiased data in AI-driven public health decision-making.

For AI systems to make accurate predictions and address public health challenges equitably, high-quality data are paramount. As highlighted by Habehh and Gohel<sup>24</sup> and Olawade et al.,<sup>25</sup> reliable health care and public health outcomes depend on high-quality data inputs. Without clean, representative data sets, AI models run the risk of producing flawed predictions, potentially leading to ineffective or harmful decisions. Therefore, rigorous data collection, cleaning, and validation processes are prerequisites for realizing the potential of AI in public health.

Equally important is addressing data bias to prevent skewed AI-driven outcomes that may disproportionately affect certain populations. Vokinger et al. outline various strategies to identify and mitigate bias, including adjusting for confounding variables, employing debiasing algorithms, and ensuring diverse and representative training data.<sup>26</sup> Failure to address these biases can exacerbate existing health care disparities, undermining AI's potential to promote health equity. Examples of initiatives addressing these challenges include IBM Watson Health's Oncology Data Initiative, which is working with cancer institutes to create diverse data sets,<sup>27</sup> and the National Institute of Health's All of Us Research Program, which aims to collect health data from underrepresented populations in the United States.<sup>28</sup>

### Step 3: Implementing Standard Dual-Use Controls

AI technologies in public health have dual-use implications, offering the potential for both beneficial applications, such as disease outbreak prediction,

and harmful applications, such as the creation of bioweapons. To protect public health and ensure the responsible use of AI, it is imperative to implement standardized dual-use controls. The objective of step 3 is to implement standard controls to ensure that potential uses are accounted for and that misuse is limited.

The dual-use nature of AI technologies in public health necessitates robust controls to prevent misuse while ensuring safe applications. Research by Urbina et al. highlighted the importance of safeguards in AI-driven drug discovery,<sup>29</sup> and the Defense Advanced Research Projects Agency's Explainable AI program aims to create interpretable AI systems for sensitive applications. Whittlestone et al. provided a framework for developing dual-use control standards, addressing ethical and societal implications of AI.<sup>30</sup> Recent work by Ning et al. focused on ethical considerations for generative AI in health care.<sup>31</sup> Practical implementations—such as OpenAI's strict use policy for Generative Pre-trained Transformer 3 (GPT-3), which limits the generation of harmful content—demonstrate how clear policies can mitigate dual-use risks.

### Step 4: Enhancing AI Reliability

Human oversight of AI applications, particularly in public health, is crucial to ensure ethical, fair, and accountable decision-making. The objective of step 4 is to improve AI reliability in public health through continuous human feedback.

Integrating human expertise into AI systems is critical to maintaining trust and reliability in public health initiatives. As highlighted by Díaz-Rodríguez et al., human oversight ensures ethical and

responsible decision-making in AI.<sup>32</sup> For example, Google's breast cancer screening AI incorporates feedback from radiologists to improve accuracy, exemplifying a human-in-the-loop approach. Ongoing human input is essential for refining AI systems to address complex public health challenges. Human experts provide essential context, domain knowledge, and oversight that AI alone cannot, ensuring ethical, fair, and accountable decisions.<sup>33</sup> Although integrating human feedback requires careful design and resources, it is critical to building trust. Microsoft's AI for Accessibility program illustrates this approach, using human input to improve tools such as the Seeing AI app for visually impaired users.

### Step 5: Building Infrastructure for AI Models

A robust AI infrastructure is a critical prerequisite for implementing AI solutions in public health. It includes not only the technical hardware and software, but also the organizational capacity to maintain, update, and manage AI systems. Without adequate infrastructure, even the most advanced AI algorithms cannot be used effectively to address public health challenges. The objective of step 5 is to build robust infrastructure for AI model training and testing.

Building a robust AI infrastructure for public health requires two key components: a strong technical foundation and organizational capacity. The technical foundation includes powerful computing resources, data management systems, and software frameworks for model training and deployment, as highlighted by Zhang et al.<sup>34</sup> Organizational capacity includes skilled personnel, governance structures, and processes for data

security and privacy, as discussed by Shimonski<sup>35</sup> and Dixon and Grannis.<sup>36</sup> This comprehensive infrastructure is critical for the effective implementation of AI solutions in public health, enabling secure model training and testing while protecting data privacy, and ultimately improving population health outcomes and intervention efficiency.

## CONCLUSION

Although it is impractical to address all key challenges simultaneously, a structured approach enables stakeholders to transparently advance AI readiness in public health, address critical issues sequentially, and ensure successful AI integration for improved health outcomes and system efficiency.

The symbiosis of AI and public health is a multifaceted endeavor that requires a concerted effort to address the challenges discussed here. By fostering collaboration, implementing strong data governance, ensuring dual-use standards, integrating continuous human feedback, and investing in AI infrastructure, we can make AI a standard and transformative force in public health. This article not only addresses current challenges, but also puts forth a future where AI and public health professionals work together to improve health outcomes and enhance the delivery of health services. *AJPH*

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G. Hattab conceptualized the editorial, wrote the entire piece, reviewed and edited for technical accuracy, ensured that all claims were substantiated, and articulated the five key steps, the validation board, and the hierarchical mind map. C. Irrgang edited the editorial for clarity and coherence and ensured that complex ideas were accessible. N. Körber edited the editorial for clarity and provided specific case studies to illustrate key points in the editorial. D. Kühnert offered critical feedback on the draft. K. Ladewig provided critical feedback on the draft and suggested additional references.

## CONFLICTS OF INTEREST

The authors declare no competing interests.

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