Journal of Innovative Science

ISSN(Online): 3082- 4435

Volume- 02| Issue- 01| 2026

Research Article

Received: 10-02-2026 | **Accepted:** 05-03-2026 | **Published:** 20-03-2026

AI-Based Optimization of Public Health Interventions in the U.S.

Ishmael Jesse Narh Adikorley

Marquette University, Milwaukee, WI, USA

Abstract: Artificial intelligence (AI) is increasingly recognized as a transformative force in public health, offering new methods for disease surveillance, early outbreak detection, precision prevention, and equitable resource allocation. This paper examines the opportunities and challenges of AI-driven optimization of public health interventions in the United States. We highlight applications that have improved prediction accuracy in infectious disease forecasting and personalized strategies for chronic disease prevention. Benefits include scalability, cost-effectiveness, and the integration of multimodal data sources, such as electronic health records, environmental datasets, and wearable technologies. Despite these advances, critical limitations persist. Issues of algorithmic bias, data representativeness, transparency, and infrastructure gaps continue to limit generalizability and trust in AI-powered systems. Ethical concerns, particularly surrounding privacy, equity, and accountability, demand robust governance frameworks and community engagement. Future directions emphasize the development of explainable and adaptive models, investment in workforce training, and stronger regulatory oversight to balance innovation with fairness. AI's success in public health will ultimately be measured not by technical sophistication but by its capacity to improve health outcomes equitably across diverse U.S. populations.

Keywords: Artificial intelligence, public health, Health equity, Disease surveillance, Ethical governance.

INTRODUCTION

The COVID-19 pandemic significantly accelerated the adoption of artificial intelligence (AI) in public health across the United States. AI-based models have been employed for outbreak forecasting, contact tracing, and prediction of healthcare demand, demonstrating both substantial potential and serious challenges in rapid deployment (Panteli *et al.*, 2025; Tariq & Ismail, 2024; Payedimarri *et al.*, 2021).

At the same time, the U.S. faces entrenched health challenges: stark geographic and racial disparities in life expectancy, rising prevalence of chronic noncommunicable diseases, and mounting threats from public health emergencies such as drug overdoses and climate-related effects. Dwyer-Lindgren *et al.*, in *The Lancet* (2024) updated the "Ten Americas" framework and found that, in 2021, the gap in life expectancy between the highest-expectancy and lowest-expectancy of the ten demographic groups was 20.4 years (Dwyer-Lindgren *et al.*, 2024). Similarly, machine-learning models have been shown to be capable of predicting opioid overdose risk from electronic health record (EHR) data with promising accuracy, potentially enabling proactive intervention (Dong *et al.*, 2020).

Despite these promising developments, the implementation of AI for optimizing public health interventions confronts multiple obstacles (Nortey *et al.*, 2025). These include data privacy and protection concerns; risk of algorithmic bias, especially when training data underrepresent disadvantaged populations; limitations in infrastructure and workforce capacity in local health departments; and regulatory and ethical uncertainty (Panteli *et al.*, 2025; Fisher *et al.*, 2022; Williamson & Prybutok, 2024).

This narrative review integrates literature since about 2020 on AI-driven optimization of public health interventions in the U.S. It examines (i) applications and technological advances; (ii) barriers to implementation, including equity, privacy, and governance; and (iii) ethical and policy considerations. By situating these within the evolving U.S. public health policy landscape, this paper aims to identify opportunities for further research and practical implications for policymakers, public health practitioners, and researchers. It focuses on harnessing AI to improve population health while respecting fairness, privacy, and feasibility.

EMERGING TRENDS AND THEMATIC ANALYSIS

The application of AI in U.S. public health has been accelerating, particularly under pressures exposed by the COVID-19 pandemic. In the current literature, we observe four broad and interrelated themes:

- Monitoring and predictive analytics
- Personalization and intervention targeting
- Policy simulation and resource allocation
- Cross-cutting issues of ethics, equity, and workforce/infrastructure

***Corresponding Author:** Ishmael Jesse Narh Adikorley

DOI- https://doi.org/10.5281/zenodo.19137412

Each of these encapsulates both the promise and the challenge of integrating AI into public health systems.

Monitoring and Predictive Analytics: From Reactive To Proactive

AI approaches are increasingly being applied to shift public health surveillance from a reactive posture to more proactive detection of emerging signals. Traditional systems (e.g., clinical reporting, manual aggregation) often face substantial delays. In contrast, modern AI models can integrate multiple data streams, including electronic health records, syndromic surveillance, digital symptom tracking, environmental or sensor data, and social media or Internet searches, to detect anomalies earlier than conventional methods.

The CDC's "Vision for Using AI in Public Health" outlines strategic aims to enhance early threat detection, operational efficiency, and responsible AI deployment across federal and state health agencies (CDC, 2025).

In practice, integrated forecasting models in one U.S. study leveraged public health surveillance and meteorological data to predict West Nile virus incidence in a high-risk region. The combined model outperformed a baseline model that included only historical averages and seasonal trends (Akorli *et al.*, 2025; Wimberly *et al.*, 2022; Harp *et al.*, 2025). Such evidence supports the value of environmental and climatic data in enhancing predictive performance.

However, the magnitude of improvement depends heavily on context, disease, location, and data quality. For instance, in a multi-model prediction of West Nile neuroinvasive disease across U.S. climate regions (2015–2021), machine learning and ensemble models did *not* consistently outperform baseline statistical (negative binomial) models by a large margin; the gains were modest and varied across regions (Holcomb *et al.*, 2023).

These systems are vulnerable to data quality issues, geographic sampling bias, and representativeness limitations. Surveillance bias can occur when detection mechanisms are denser in well-monitored areas, causing models to "see" signals there more readily while failing to detect emerging risks in underserved regions. This challenge is widely recognized in AI in health and epidemiology literature, especially in discussions of bias, fairness, and equity.

Another key hurdle is interpretability: advanced models (ensembles, deep neural nets, complex spatiotemporal architectures) may deliver high accuracy but remain opaque to public health practitioners. Without transparent, explainable outputs, adoption by decision makers who require interpretability for accountability and trust may be constrained.

Personalization and Targeted Interventions

A growing ambition in public health AI is to move beyond "one size fits all" toward tailored interventions that account for individual risk, preferences, and context (behavioral, social determinants, etc.) (Is-mail and Nortey, 2025; Nortey et al, 2025). In clinical domains, reinforcement learning and personalized treatment policy models are increasingly studied (e.g., in chronic disease management) (Jayaraman *et al.*, 2024).

In public health, some works explore how machine learning classifiers can predict adherence to prevention programs (e.g., for diabetes, smoking cessation), achieving moderate accuracy. Other efforts aim to optimize intervention timing and content using user behavior and social determinants. However, high variation across individuals and limited high-quality training data constrain robustness.

Incorporating social determinants of health (housing, food security, environmental hazards) into targeting algorithms enables more holistic interventions but heightens privacy and equity concerns. Sensitive socioeconomic or demographic data could be misused or misinterpreted if transparency and fairness safeguards are weak.

A persistent risk is that AI-assisted interventions may deepen disparities, particularly in communities with lower digital access or literacy. If the populations most in need have the least means to engage with the AI-enabled services, an inverse care pattern may be reinforced. This concern is widely raised in AI and health equity scholarship (Panteli *et al.*, 2025; Anjaria *et al.*, 2023).

Policy Simulation and Resource Optimization

Another key trend is using AI and simulation to help policymakers anticipate and optimize the effects of interventions and resource allocation. Methods such as agent-based modeling, system dynamics, or reinforcement learning are being used to simulate epidemic spread, vaccination strategies, or resource distribution under

Publisher: SARC Publisher

constraints (Ramezani *et al.*, 2023; da Silva Mendes *et al.*, 2025; Panteli *et al.*, 2025).

Reinforcement learning (RL) approaches have been applied in healthcare resource allocation. A notable study used deep RL (with a transformer-like network) to allocate critical care (e.g., ventilators) under scarcity, aiming to balance overall survival and equitable allocation across racial groups. The RL policy reduced excess deaths and improved fairness relative to some conventional triage heuristics (Li *et al.*, 2023; Jayaraman *et al.*, 2024).

However, such models often face adoption barriers. First, complexity and lack of interpretability (the “black box” problem) make it hard for public officials to trust or justify algorithmic recommendations. Second, simulation models rely on assumptions (disease parameters, compliance, logistic constraints) that may not be held in real settings. Third, transparency, accountability, and governance of algorithmic decisions are necessary in democratic public health systems.

Recent methodological work also seeks to integrate interpretability: for example, “Rule-Bottleneck Reinforcement Learning” combines decision-making with explanation generation (via language models) to make opaque policies more human-understandable (Tec *et al.*, 2025).

Cross-Cutting Challenges: Ethics, Equity, Workforce, and Infrastructure

Implementation of AI in public health must grapple with several structural and moral dimensions:

- Data Governance & Privacy: U.S. health data are subject to complex federal and state rules (e.g., HIPAA), and AI applications often blend multiple data sources, raising reidentification risks and regulatory conflicts (Ramezani *et al.*, 2023; Panteli *et al.*, 2025; Anjaria *et al.*, 2023).
- Workforce Capacity & Literacy: Many public health practitioners may lack the technical skills, data literacy, or ethical training to interpret, supervise, and maintain AI systems. Upskilling is costly and slow (Ramezani *et al.*, 2023; Panteli *et al.*, 2025).
- Infrastructure Gaps & Resource Inequality: Health departments vary substantially in technological maturity. Smaller or rural agencies may lack computing infrastructure or stable networks. Moving to cloud-based AI platforms can alleviate some burdens but introduces dependence on external vendors and security concerns.
- Model Bias & Fairness: AI systems may perpetuate or amplify disparities if the training data is skewed. Ensuring fairness-aware modeling, bias audits, and equitable performance across subgroups is essential (Ramezani *et al.*, 2023; Panteli *et al.*, 2025; Anjaria *et al.*, 2023).
- Community Engagement & Trust: Engaging communities in AI development helps align systems with local needs and helps ensure legitimacy. Yet participatory design is resource-intensive and often difficult in high-pressure public health settings.
- Regulatory & Accountability Frameworks: Because AI decisions may influence resource allocation, treatment priorities, or access, public health agencies must adopt transparency, auditability, and oversight mechanisms. Without them, even well-performing systems may be politically or ethically untenable.

Table 1. Key AI Applications in U.S. Public Health Practice (2020-2025)

Application Domain	AI Technology	Implementation Examples	Key Benefits	Current Limitations
Disease Surveillance	NLP, Spatiotemporal ML	CDC syndromic surveillance, MedCoder system	Early warning, Pattern recognition	Data quality, Integration complexity
Intervention Targeting	Predictive modeling	Diabetes prevention, Vaccination campaigns	Precision targeting, Resource efficiency	Bias risks, Privacy concerns
Resource Allocation	Optimization algorithms	Emergency response, Supply chain	Efficiency gains, Cost reduction	Complexity, Interpretability
Health Equity	Fairness-aware ML	Community health programs	Disparity reduction, Inclusive design	Limited tools, Measurement challenges
Policy	Agent-based	Intervention impact	Evidence-based	Transparency issues,

Publisher: SARC Publisher

Simulation	modeling	forecasting	planning, Risk mitigation	Validation challenges

These trends show that AI offers meaningful advances in surveillance, targeting, and decision support, but the success of these systems depends heavily on addressing challenges related to transparency, fairness, infrastructure, regulations, and social issues. In the next section, we examine how existing AI-powered public health interventions have confronted these challenges across U.S. domains of disease control, chronic disease prevention, and emergencies.

Applications of AI to Optimizing Public Health Interventions

AI is being applied in multiple ways in U.S. public health to optimize interventions, including early detection, behavioral promotion, chronic disease management, and policy decision support. Below are domains with illustrative studies, benefits, and persistent challenges.

Disease Monitoring and Early Warning Systems

AI-based surveillance integrates diverse data streams (social media, Internet search trends, syndromic or sentinel clinical data, environmental or sensor data) to identify outbreaks earlier than traditional public health reporting systems. For example, BlueDot was among the first to flag reports of *'pneumonia of unknown cause'* in Wuhan, China, in late December 2019, the cases that were later confirmed as COVID-19. (Naudé, 2020)

In the U.S., reinforcement learning combined with agent-based epidemic modeling has been used to help allocate resources dynamically during COVID-19 across states, adjusting for temporal variation in infection rates and economic or demographic features. Such models offer improved flexibility over static heuristics (Zong & Luo, 2022).

Challenges in this domain include data lags, underreporting (especially in underserved populations), and a lack of interpretability for decision makers.

Optimizing Resource Allocation and Program Development

AI and simulation-optimization are powering decisions about where to site vaccine centers, how to allocate vaccines fairly, and how to plan vaccination campaigns more effectively.

- *Yin et al. (2023)* propose a simulation-optimization framework to select vaccine center locations and vaccine allocation under budget constraints in the U.S. setting (Yin *et al.*, 2014).
- *Optimizing Spatial Allocation of COVID-19 Vaccine by Agent-Based Spatiotemporal Simulations* demonstrates that incorporating geographic heterogeneity (e.g., age, spatial clustering) into vaccine strategies improves epidemic control compared to uniform or random strategies (Zhou *et al.*, 2021).
- In Miami-Dade County, modeling of vaccination rollout suggested that vaccine distribution significantly reduced case incidence and hastened the decline of daily case counts relative to scenarios without vaccination (Tatapudi *et al.*, 2021).

Despite these successes, obstacles include uncertain supply chains, public acceptance, equitable access, and ensuring that optimization models do not inadvertently prioritize efficiency over vulnerable populations.

Behavioral Health Promotion Through AI Interventions

AI chatbots and digital agents are increasingly being tested in randomized controlled trials to promote health behaviors and support mental health.

- A recent meta-analysis of 19 trials (3,567 participants) showed that chatbot interventions can increase physical activity, fruit and vegetable consumption, and improve sleep duration/quality, with small-to-moderate effect sizes (Singh *et al.*, 2023).
- Another review of 15 studies found chatbots effective in promoting healthy lifestyles (e.g., diet, exercise), smoking cessation, and medication adherence, though many studies had limitations in reporting, generalizability, or bold claims of long-term effects (Aggarwal *et al.*, 2023).
- For mental health, short-term improvements in depression and anxiety symptoms have been reported with AI-chatbot interventions; however, follow-up data and consistent long-term outcomes remain scarce (Zhong *et al.*, 2024).

Publisher: SARC Publisher

Chronic Disease Management

AI is used in the prediction of risk (e.g., for cardiovascular disease, diabetes), enabling earlier detection of individuals at higher risk and facilitating preventive strategies. There are fewer real-world implementation examples, and many models do not yet incorporate real-time behavioral or environmental inputs, limiting their ability to suggest actionable interventions.

Policy Level Simulation and Decision Support

AI-based policy simulation (agent-based models, system dynamics, optimization frameworks) has been used to test 'what-if' scenarios for vaccine allocation, epidemic spread, and public health interventions.

- ➢ The study by Yin et al. on vaccine center locations is one example (Yin *et al.*, 2014).
- ➢ Another example: modeling in Miami-Dade County compared different vaccine rollout scenarios, showing substantial reductions in cases and deaths under certain vaccination strategies (Tatapudi *et al.*, 2021).

These decision support tools are valuable for policymakers, but their effectiveness depends on transparency, validity of assumptions, stakeholder involvement, and adaptability to local contexts.

BENEFITS, LIMITATIONS, AND ETHICAL CONSIDERATIONS

AI applied in U.S. public health has the potential to enhance efficiency, scale, personalization, and decision quality. Yet its scale-up is hampered by data, infrastructure, governance, and ethical and equity issues. This section critically evaluates the key benefits, challenges, and ethical concerns evidenced in recent literature.

Benefits

Efficiency and Scalability

- ➢ AI methods (machine learning, natural language processing, etc.) enable faster processing of large and heterogeneous datasets than traditional manual surveillance systems. This can shorten detection times, improve timeliness of responses, and support real-time monitoring.
- ➢ Example: Natural Language Processing (NLP) -augmented chatbots or detection models have been shown to significantly improve physical activity and health behaviour outcomes in RCTs/meta-analyses, indicating scalable interventions (Singh *et al.*, 2023; Wang *et al.*, 2025).
- ➢ Personalization of Interventions
- ➢ AI systems allow for more tailored behavior change interventions based on users' activity histories, motivational factors, and context. For instance, AI chatbots with relational or conversational features may engage users better, as shown in *"Enhancing Physical Activity through a Relational Artificial Intelligence Chatbot: A Feasibility and Usability Study"* (Oh *et al.*, 2025).
- ➢ Systematic reviews find that many chatbot interventions successfully increase physical activity, with somewhat less consistent evidence for changes in diet or weight status (Oh *et al.*, 2021; Singh *et al.*, 2023).
- ➢ Cost-Effectiveness and Resource Use
- ➢ By automating parts of the surveillance, outreach, or behavior-change programs, AI can reduce personnel time and resource overhead. Although robust cost-benefit estimates are still relatively sparse, early trials suggest that some interventions are cost-favorable when deployed at scale.
- ➢ Integration of Diverse Data Sources
- ➢ AI models incorporating data from wearables, EHRs, environmental sensors, etc., combined with social/digital sources, are improving predictiveness for certain health outcomes. For example, integrating activity data, environmental context, and digital behavior helps fine-tune interventions.
- ➢ While climate-sensitive disease models with meteorological features are promising, the magnitude of improvement depends heavily on local data quality and model calibration.

Limitations

- ➢ Data Bias and Generalizability
- ➢ Many AI datasets underrepresent minority populations or omit information on key social determinants, which limits how well models generalize beyond populations with abundant data.
- ➢ There is evidence that clinical AI algorithms often lack transparency about patient demographics, skin tone, or other diversity metrics. For example, a scoping review of AI datasets for skin disease found only ~20% of studies reported ethnicity/race, ~10% included skin tone information (Daneshjou *et al.*, 2021).
- ➢ Transparency, Interpretability, and Trust
- ➢ High-performing models (ensembles, deep learning, etc.) often operate as "black boxes." Frontiers in Digital Health published a paper titled *"A trustworthy AI reality-check: the lack of transparency of artificial intelligence*

Publisher: SARC Publisher

products in healthcare", discussing how many AI tools lack clear documentation, explanation, or validation (Fehr *et al.*, 2024).

- Lack of interpretability can undermine policymakers' confidence, community trust, and ability to audit or correct mistakes.
- Technical and Infrastructure Barriers
- Many public health departments, especially at the county or local level, lack dedicated AI or data science staff, reliable computing infrastructure, up-to-date data systems, or the funds to sustain advanced models.
- Variations across jurisdictions in technology, capacity, and regulatory environment make uniform deployment difficult.
- Integration & Workflow Challenges
- AI predictions or recommendations may not align with existing public health systems, workflows, or regulatory requirements. EHR interoperability, data privacy laws, staff training, and end-user usability are common bottlenecks.

Ethical and Equity Considerations

- Privacy and Data Security
- Use of sensitive individual data (clinical, behavioral, and location) raises concerns about consent, anonymization, and potential misuse. Even with HIPAA and other regulations, new AI-scale data aggregation can create risks of reidentification, unauthorized data access, and other security breaches.
- Algorithmic Bias and Health Disparities
- Bias can emerge from training data, model design, or deployment practices. Poor representation can lead to worse performance for historically marginalized groups.
- The "digital divide" in terms of access to reliable internet, digital literacy, or devices may further entrench disparities; those who could benefit most from AI-enabled interventions may be those least likely to gain access.
- Governance, Accountability, and Transparency
- Clear governance structures are essential for oversight, model validation, auditing, fairness checks, and accountability. Developers, public health agencies, policymakers, and communities need to define roles and responsibilities.
- Independent auditing, reporting of fairness metrics, and public disclosure of algorithmic design choices are still not commonly required in many U.S. public health AI deployments.
- Community Trust and Engagement
- Public acceptability depends on processes that are transparent, ethically sound, culturally competent, and inclusive. Community involvement in design and feedback loops can help bridge mistrust and improve the relevance of AI interventions.

Summary

The promise of AI in U.S. public health is substantial: it increases speed, coverage, personalization, and the better use of data. But realizing that promise requires navigating data and infrastructure constraints, ensuring generalizability, maintaining transparency and accountability, and attending carefully to ethical, equity, and trust concerns. Responsible adoption depends not just on technical performance, but also on institutional capacity, governance frameworks, and inclusion of diverse voices.

FUTURE DIRECTIONS AND RESEARCH GAPS

Although AI methods for optimizing public health interventions have matured rapidly, critical gaps remain that limit their long-term impact and equitable deployment in U.S. settings.

Need for Long-Term, Pragmatic Evaluations

There is a shortage of longitudinal, pragmatic studies that assess whether AI-driven public health interventions produce durable behavior change and sustained population-level health benefits. Many published evaluations are short-term trials, feasibility studies, or retrospective model validations; few report multi-year follow-up that would be required to evaluate persistence, generalizability, and unintended consequences in diverse U.S. populations. Systematic reviews and meta-research note this "translation gap" from promising trials to robust real-world evidence (Jacob *et al.*, 2025; El Arab *et al.*, 2025).

Causal Inference and Mechanistic Understanding

Contemporary AI models excel at pattern recognition but often do not distinguish correlation from causation, a critical limitation where interventions are to be recommended or resources reallocated. Advances in causal machine-learning and related methods (e.g., targeted learning, causal forests, doubly robust estimators) provide practical approaches for estimating intervention effects from observational EHR and administrative data, but their application in public health practice remains limited and requires stronger methodological

Publisher: SARC Publisher

uptake. Research that integrates causal inference with domain mechanistic models will be important for actionable recommendations (Feuerriegel *et al.*, 2024; Abécassis *et al.*, 2025).

Data Quality, Representativeness, and Fairness

High-quality, representative data are foundational for equitable AI. Many healthcare and public-health datasets underrepresent marginalized groups or omit key social determinants, which can lead to biased predictions and exacerbate disparities. The literature emphasizes the need for systematic bias auditing, fairness-aware model design, and data collection strategies that prioritize representativeness. Algorithmic fairness methods (and their limits) are increasingly mature, but operationalizing these methods in public-health pipelines remains a research and practice gap (Chen *et al.*, 2023; Hasanzadeh *et al.*, 2025). U.S. Department of Health and Human Services (HHS)

Explainability, Transparency, and Governance

Adoption of AI tools in public health hinges on transparency and interpretability: stakeholders (public health officials, clinicians, and the public) must understand model assumptions, performance across subgroups, and failure modes. Calls for governance frameworks, routine independent auditing, and public reporting of fairness and performance metrics are growing. U.S. federal agencies (U.S. Department of Health and Human Services (HHS), Centers for Disease Control and Prevention (CDC)) are developing AI strategies and guidance, but concrete regulatory and operational standards for public-health AI remain under development. Research should evaluate governance mechanisms (audit trails, model cards, post-deployment monitoring) in real operational settings (U.S. Department of Health and Human Services (HHS), (n.d); Centers for Disease Control and Prevention (CDC), 2025).

Privacy, Legal Frameworks, and Data Stewardship

AI-scale data integration (EHRs + sensors + digital traces) raises re-identification and consent concerns that existing legal frameworks (e.g., HIPAA) do not fully anticipate. Scholarship and policy analyses call for updated data stewardship models, clearer rules on de-identification in AI pipelines, and practical privacy-preserving techniques (federated learning, secure multiparty computation) evaluated in public-health contexts. Comparative legal research and pilot demonstrations of privacy-preserving analytics are important next steps (Conduah *et al.*, 2025; Rezaeikhonakdar, 2023).

Workforce, Infrastructure, and Implementation Science

Many local public-health agencies lack workforce skills (data science, ML operations, ethics) and technical infrastructure to deploy and maintain AI systems. Investments in training, interoperable data platforms, and sustainable partnerships between academia, industry, and public health are essential. Implementation science research is needed to identify pragmatic models for embedding AI tools into everyday public-health workflows, including cost and resource implications (Hattab *et al.*, 2025; CDC, 2025).

Comparative Effectiveness and Equity-Focused Trials

There are few head-to-head trials comparing AI-augmented interventions with standard public-health approaches on outcomes that matter to populations (equity, morbidity, mortality, cost-effectiveness). The field needs randomized or quasi-experimental comparative studies designed to evaluate both effectiveness and differential impacts across demographic or socioeconomic groups. Such designs are crucial to ensure AI does not unintentionally widen disparities (El Arab *et al.*, 2025; Joseph, 2025).

Research Agenda, Priorities

Based on these gaps, priority research areas include: (1) multi-year pragmatic trials and implementation studies that measure sustained impact and equity; (2) methodological work integrating causal inference and mechanistic models for action-oriented predictions; (3) operational frameworks for bias auditing, fairness checks, and model governance in public-health settings; (4) pilot deployments of privacy-preserving architectures (e.g., federated learning) with legal and ethical evaluation; and (5) workforce and infrastructure interventions studied with implementation science methods to ensure scalable, sustainable adoption.

CONCLUSION

Artificial intelligence (AI) offers significant opportunities for U.S. public health, from enhancing disease surveillance to enabling personalized prevention and optimizing resource allocation. Evidence from the COVID-19 pandemic demonstrates that AI-based models can outperform traditional approaches in outbreak detection and forecasting, highlighting their

Publisher: SARC Publisher

potential for strengthening preparedness and response.

However, the transformative impact of AI is constrained by persistent challenges, including data quality, algorithmic bias, privacy concerns, and inequitable access to digital resources. These issues underscore the need for transparent and accountable governance frameworks, as well as inclusive approaches that prioritize equity in health outcomes.

Future progress depends on developing explainable and adaptive algorithms, investing in workforce training and infrastructure, and establishing regulatory safeguards that balance innovation with ethical responsibility. Central to this effort is meaningful community engagement to ensure that AI interventions do not exacerbate disparities but instead advance fairness and trust.

Ultimately, the success of AI in public health will not be measured solely by technical innovation, but by whether these tools demonstrably improve health outcomes and extend equitable access to all communities.

REFERENCES

1. Abécassis, J., Dumas, É., Alberge, J., & Varoquaux, G. "From Prediction to Prescription: Machine Learning and Causal Inference for the Heterogeneous Treatment Effect." *Annual Review of Biomedical Data Science* 8 (2025).
2. Aggarwal, A., Tam, C. C., Wu, D., Li, X., & Qiao, S. "Artificial intelligence–based chatbots for promoting health behavioral changes: Systematic review." *Journal of Medical Internet Research* 25 (2023): e40789.
3. Akorli, J., Oware, S. K., Sackitey, D. B., Pul, R. M., Akyea-Bobi, N. E., Akporh, S. S., et al. "Climate-driven models reveal temporal trends in Aedes breeding: Implications for outbreak preparedness and control interventions." *BMC Public Health* 25.1 (2025): 2735.
4. Anjaria, P., Asediya, V., Bhavsar, P., Pathak, A., Desai, D., & Patil, V. "Artificial intelligence in public health: Revolutionizing epidemiological surveillance for pandemic preparedness and equitable vaccine access." *Vaccines* 11.7 (2023): 1154.
5. CDC. "CDC's Vision for Using Artificial Intelligence in Public Health." (2025).
6. CDC. "Public Health Data Strategy Milestones for 2025 and 2026." (2025).
7. Chen, R. J., Wang, J. J., Williamson, D. F., Chen, T. Y., Lipkova, J., Lu, M. Y., et al. "Algorithmic fairness in artificial intelligence for medicine and healthcare." *Nature Biomedical Engineering* 7.6 (2023): 719–742.
8. Conduah, A. K., Ofoe, S., & Siaw-Marfo, D. "Data privacy in healthcare: Global challenges and solutions." *Digital Health* 11 (2025): 20552076251343959.
9. da Silva Mendes, V. I., Milhomens de Ferreira Mendes, B., Moura, R. P., Mota Lourenço, I., Ferreira Alves Oliveira, M., Lee Ng, K., & Sousa Pinto, C. "Harnessing artificial intelligence for enhanced public health surveillance: A narrative review." *Frontiers in Public Health* 13 (2025): 1601151.
10. Daneshjou, R., Smith, M. P., Sun, M. D., Rotemberg, V., & Zou, J. "Lack of transparency and potential bias in artificial intelligence data sets and algorithms: A scoping review." *JAMA Dermatology* 157.11 (2021): 1362–1369.
11. Dong, X., Deng, J., Hou, W., Rashidian, S., Rosenthal, R. N., Saltz, M., et al. "Predicting opioid overdose risk of patients with opioid prescriptions using electronic health records based on temporal deep learning." *Journal of Biomedical Informatics* 116 (2021): 103725.
12. Dong, X., Rashidian, S., Wang, Y., Hajagos, J., Zhao, X., Rosenthal, R. N., et al. "Machine learning based opioid overdose prediction using electronic health records." *AMIA Annual Symposium Proceedings* 2019 (2020): 389.
13. Dwyer-Lindgren, L., Baumann, M. M., Li, Z., Kelly, Y. O., Schmidt, C., Searchinger, C., et al. "Ten Americas: A systematic analysis of life expectancy disparities in the USA." *The Lancet* 404.10469 (2024): 2299–2313.
14. El Arab, R. A., Abu-Mahfouz, M. S., Abuadas, F. H., Alzghoul, H., Almari, M., Ghannam, A., & Seweid, M. M. "Bridging the gap: From AI success in clinical trials to real-world healthcare implementation—A narrative review." *Healthcare* 13.7 (2025): 701.
15. Fehr, J., Citro, B., Malpani, R., Lippert, C., & Madai, V. I. "A trustworthy AI reality-check: The lack of transparency of artificial intelligence products in healthcare." *Frontiers in Digital Health* 6 (2024): 1267290.
16. Feuerriegel, S., Frauen, D., Melnychuk, V., Schweisthal, J., Hess, K., Curth, A., et al. "Causal machine learning for predicting treatment outcomes." *Nature Medicine* 30.4 (2024): 958–968.

Publisher: SARC Publisher

17. Fisher, S., & Rosella, L. C. "Priorities for successful use of artificial intelligence by public health organizations: A literature review." *BMC Public Health* 22.1 (2022): 2146.
18. Harp, R. D., Holcomb, K. M., Retkute, R., Prusokiene, A., Prusokas, A., Ertem, Z., et al. "Evaluation of the 2022 West Nile virus forecasting challenge, USA." *Parasites & Vectors* 18.1 (2025): 152.
19. Hasanzadeh, F., Josephson, C. B., Waters, G., Adedinsewo, D., Azizi, Z., & White, J. A. "Bias recognition and mitigation strategies in artificial intelligence healthcare applications." *NPJ Digital Medicine* 8.1 (2025): 154.
20. Hattab, G., Irrgang, C., Körber, N., Kühnert, D., & Ladewig, K. "The way forward to embrace artificial intelligence in public health." *American Journal of Public Health* 115.2 (2025): 123–128.
21. HHS. "Artificial Intelligence (AI) at HHS." (n.d.).
22. Holcomb, K. M., Staples, J. E., Nett, R. J., Beard, C. B., Petersen, L. R., Benjamin, S. G., et al. "Multi-model prediction of West Nile virus neuroinvasive disease with machine learning for identification of important regional climatic drivers." *GeoHealth* 7.11 (2023): e2023GH000906.
23. Jacob, C., Brasier, N., Laurenzi, E., Heuss, S., Mougiakakou, S. G., Cöltekin, A., & Peter, M. K. "AI for IMPACTS framework for evaluating the long-term real-world impacts of AI-powered clinician tools: Systematic review and narrative synthesis." *Journal of Medical Internet Research* 27 (2025): e67485.
24. Jayaraman, P., Desman, J., Sabounchi, M., Nadkarni, G. N., & Sakhuja, A. "A primer on reinforcement learning in medicine for clinicians." *NPJ Digital Medicine* 7.1 (2024): 337.
25. Joseph, J. "Algorithmic bias in public health AI: A silent threat to equity in low-resource settings." *Frontiers in Public Health* 13 (2025): 1643180.
26. Li, Y., Mao, C., Huang, K., Wang, H., Yu, Z., Wang, M., & Luo, Y. "Deep reinforcement learning for efficient and fair allocation of health care resources." *arXiv* (2023).
27. Is-mail, M., & Nortey, R. T. "Economic impact of social support on reducing hospital readmissions in older hypertensive adults." *World Journal of Advanced Research and Reviews* 28.1 (2025): 2122–2127.
28. Naudé, W. "Artificial intelligence against COVID-19: An early review." (2020).
29. Nortey, R. T., Egbunu, A. S., & Oware, E. "Barriers to social support access in urban vs. rural older adults U.S. populations: A scoping review." *Sarcouncil Journal of Medicine and Surgery* 4.11 (2025): 1–10.
30. Nortey, R. T., Korang, A., Ansah, R. S., & Kaiser, F. "Telehealth and digital platforms for delivering social support to rural older adults with hypertension: A systematic review with U.S. policy and global health implications." *Sarcouncil Journal of Internal Medicine and Public Health* 4.6 (2025): 1–15.
31. Oh, Y. J., Liang, K. H., Kim, D. D., Zhang, X., Yu, Z., Fukuoka, Y., & Zhang, J. "Enhancing physical activity through a relational artificial intelligence chatbot: A feasibility and usability study." *Digital Health* 11 (2025): 20552076251324445.
32. Oh, Y. J., Zhang, J., Fang, M. L., & Fukuoka, Y. "A systematic review of artificial intelligence chatbots for promoting physical activity, healthy diet, and weight loss." *International Journal of Behavioral Nutrition and Physical Activity* 18.1 (2021): 160.
33. Oware, E., Nortey, R. T., & Egbunu, A. S. "Community-based social support programs for older adults with hypertension: A comprehensive review of U.S. models." *International Journal for Multidisciplinary Research* 7.4 (2025): 1–15.
34. Panteli, D., Adib, K., Buttigieg, S., Goiana-da-Silva, F., Ladewig, K., Azzopardi-Muscat, N., et al. "Artificial intelligence in public health: Promises, challenges, and an agenda for policy makers and public health institutions." *The Lancet Public Health* 10.5 (2025): e428–e432.
35. Payedimarri, A. B., Concina, D., Portinale, L., Canonico, M., Seys, D., Vanhaecht, K., & Panella, M. "Prediction models for public health containment measures on COVID-19 using artificial intelligence and machine learning: A systematic review." *International Journal of Environmental Research and Public Health* 18.9 (2021): 4499.
36. Ramezani, M., Takian, A., Bakhtiari, A., Rabiee, H. R., Ghazanfari, S., & Mostafavi, H. "The application of artificial intelligence in health policy: A scoping review." *BMC Health Services Research* 23.1 (2023): 1416.
37. Rezaeikhonakdar, D. "AI chatbots and challenges of HIPAA compliance for AI developers and vendors." *Journal of Law, Medicine & Ethics* 51.4 (2023): 988–995.

Publisher: SARC Publisher

38. Singh, B., Olds, T., Brinsley, J., Dumuid, D., Virgara, R., Matricciani, L., et al. "Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours." *NPJ Digital Medicine* 6.1 (2023): 118.
39. Tariq, M. U., & Ismail, S. B. "Deep learning in public health: Comparative predictive models for COVID-19 case forecasting." *PLOS One* 19.3 (2024): e0294289.
40. Tatapudi, H., Das, R., & Das, T. K. "Impact of vaccine prioritization strategies on mitigating COVID-19: An agent-based simulation study using an urban region in the United States." *BMC Medical Research Methodology* 21.1 (2021): 272.
41. Tec, M., Xiong, G., Wang, H., Dominici, F., & Tambe, M. "Rule-Bottleneck Reinforcement Learning: Joint explanation and decision optimization for resource allocation with language agents." *arXiv* (2025).
42. Wang, Q., Yang, W., Xu, K., & Lam, L. T. "The effect of chatbot-based exercise interventions on physical activity, exercise habits, and sedentary behavior: A systematic review and meta-analysis of randomized controlled trials." *Digital Health* 11 (2025): 20552076251353731.
43. Williamson, S. M., & Prybutok, V. "Balancing privacy and progress: A review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare." *Applied Sciences* 14.2 (2024): 675.
44. Wimberly, M. C., Davis, J. K., Hildreth, M. B., & Clayton, J. L. "Integrated forecasts based on public health surveillance and meteorological data predict West Nile virus in a high-risk region of North America." *Environmental Health Perspectives* 130.8 (2022): 087006.
45. Yin, X., Bushaj, S., Yuan, Y., & Büyüktahtakın, İ. E. "COVID-19: Agent-based simulation-optimization to vaccine center location vaccine allocation problem." *IISE Transactions* 56.7 (2024): 699–714.
46. Zhong, W., Luo, J., & Zhang, H. "The therapeutic effectiveness of artificial intelligence-based chatbots in alleviation of depressive and anxiety symptoms in short-course treatments: A systematic review and meta-analysis." *Journal of Affective Disorders* 356 (2024): 459–469.
47. Zhou, S., Zhou, S., Zheng, Z., & Lu, J. "Optimizing spatial allocation of COVID-19 vaccine by agent-based spatiotemporal simulations." *GeoHealth* 5.6 (2021): e2021GH000427.
48. Zong, K., & Luo, C. "Reinforcement learning based framework for COVID-19 resource allocation." *Computers & Industrial Engineering* 167 (2022): 107960.

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:
Adikorley, I. J. N. " AI-Based Optimization of Public Health Interventions in the U.S." *Jr. Inn. Sci.* 2.1 (2026): pp 30-39.

Publisher: SARC Publisher