



Published in final edited form as:

AIDS. 2025 August 01; 39(10): 1311–1321. doi:10.1097/QAD.0000000000004220.

Transformative Potential of Artificial Intelligence in US CDC HIV Interventions: Balancing innovation with health privacy

Emiko Kamitani, PhD, MPH, MS, RN¹, Linda J. Koenig, PhD, MS¹, Patrick Sullivan, PhD, DVM²

¹Division of HIV Prevention, the US Centers for Disease Control and Prevention, Atlanta, Georgia, US 30329-4027

²Rollins School of Public Health, Emory University, Atlanta, Georgia, US 30322

Keywords

HIV; artificial intelligence; machine learning; deep learning; public health

Artificial intelligence (AI) has experienced unprecedented growth, transforming the landscape of sciences and opening new frontiers in research applications and interventions [1]. AI can efficiently handle massive amounts of data that are difficult for humans to manage by leveraging advanced technologies to enable computers to simulate human learning, problem-solving, and decision-making [2–4]. Integrating AI into healthcare is not just an opportunity but a critical step toward transforming healthcare systems. Through continuous monitoring and coaching, AI has the potential to enable earlier diagnosis, tailored treatments, and more efficient follow-ups, ultimately helping to reduce healthcare costs [5]. Estimates suggest that AI could cut annual US healthcare costs by \$150 billion in 2026, primarily through decreased hospitalizations, medical visits, and treatments [5]. For HIV prevention, these savings could arise through closing gaps in the continuum of HIV prevention and care, for example, increased screening leading to earlier diagnosis, faster linkage to prevention or treatment, and support for continuous care engagement. AI can therefore play a key role in healthcare, and by extension, it's important to consider how it can shape and advance the future of public health. We focus here on its potential to improve HIV prevention.

In 2021, the World Health Organization (WHO) released guidelines on the ethics and governance of AI, emphasizing the importance of embedding ethics and human rights at the core of its design, development, and use in public health systems [6]. More recently, WHO published guidance for countries and communities to assess their preparedness for integrating AI initiatives into their public health strategies [7]. As these resources become

Corresponding author: Emiko Kamitani, ekamitani@cdc.gov.

Author Contributions:

All authors on this article meet the four criteria for authorship as identified by the International Committee of Medical Journal Editors (ICMJE); all authors have contributed to the conception and design of the study, drafted or have been involved in revising this manuscript, reviewed the final version of this manuscript before submission, and agree to be accountable for all aspects of the work.

Disclosure: There are no conflicts of interest to report or financial disclosures.

more available, the time is right for agencies, providers and communities to thoughtfully consider how AI might be most effectively utilized within HIV care.

In a previous issues of *AIDS*, we published two AI-related systematic reviews on HIV pre-exposure prophylaxis (PrEP) [8, 9]. Given the rapid evolution of AI technologies, it is essential to imagine their broader applications in HIV interventions both within and beyond PrEP. As of January 2025, a search of the US Centers for Disease Control and Prevention's (CDC) *Compendium of Evidence-Based Intervention or Best Practice for HIV Prevention* [10] yielded no interventions implementing AI. On the other hand, several HIV-related AI interventions have been registered in [ClinicalTrials.gov](https://clinicaltrials.gov) (<https://clinicaltrials.gov>), indicating that there are interventions in the research study phase. These interventions aim to use AI to improve the total number of people tested [11–13], detect comorbidities [14, 15], increase medication adherence [16], and support clinical decision-making [17]. Given this nascent but growing field, it is important to think ahead to consider what next-generation HIV prevention could possibly look like with these advanced technologies.

This editorial review will explore the methods and potentially transformative impact of AI implementation across various HIV prevention interventions and activities. As the US CDC is the United States' leading public health agency, we focus on the US CDC's key public health strategies for HIV prevention, highlighting interventions and activities primarily within the United States with some global contexts, especially in countries using the President's Emergency Plan for AIDS Relief (PEPFAR) support in their national HIV control program. Both practical applications to enhance the efficiencies of current interventions and visionary concepts will be considered. Recognizing that this is a rapidly developing field, we aim to stimulate thought on how emerging AI technologies could push HIV prevention forward to inspire continued innovation.

AI TECHNOLOGIES

Machine Learning

One of the most fundamental capacities of AI systems is machine learning (ML), which enables computers to learn from historical data and improve their performance (e.g., screening, predictive analytics) without explicit programming [2]. Unlike traditional methods, where researchers hypothesize which exposure variables matter and develop statistical models to test them, ML can automatically identify complex patterns in large datasets, such as electronic health records (EHRs), public surveys, and surveillance data, without requiring a predefined hypothesis [3]. This approach saves human time and can uncover relationships that might not be apparent through traditional methods, making it a powerful tool for public health research and decision-making by enabling more precise predictions, streamlining data analysis, and facilitating innovative approaches to treatment and prevention.

Deep Learning

Deep learning (DL) simulates the complex decision-making processes of the human brain through multilayered neural networks while ML encompasses a broad range of algorithms

that require manual feature engineering [3]. DL is particularly well-suited for tasks like natural language processing (NLP) and computer vision (CV), both of which are areas in AI where DL techniques have proven to be very effective in achieving high accuracy and performance [18]. They involve the rapid and accurate identification of complex patterns in large and unstructured datasets, including those from sources like social media [3].

NLP enables machines to understand and interpret human language. It can analyze unstructured text from social media content, online forums, and health-related websites to monitor discussions, detect misinformation, and identify emerging trends. Meanwhile, CV allows systems to extract meaningful information from digital images, videos, and other visual inputs, and provide recommendations or actionable insights upon identifying defects or problems [3]. CV could accurately detect infections and other conditions through the analysis of medical images or diagnostic tools, such as point-of-care tests and X-rays, based on the data the models have been trained on, which is a key dependency as historically this has been a source of bias.

Generative AI

Generative AI (Gen AI) represents another advanced AI technology, leveraging the DL model to create original content, including text, images, and videos [3]. While Gen AI often uses DL techniques, it can encompass a broader range of methods that extend beyond DL. Gen AI can respond to user prompts by generating human-like text or multimedia content [3]. One of the most common applications is through large language models, which focus on NLP tasks and are trained on vast amounts of text data to understand and generate text [3, 19]. Gen AI can provide personalized, real-time, 24/7 accessible, non-judgmental, and culturally sensitive advice to consumers, and interactive educational materials [9, 20, 21].

Together, these AI technologies – ML, DL including NLP and CV, and Gen AI – offer diverse applications for public health. In the following section, we review how ML, DL, and Gen AI could be used to enhance HIV prevention by highlighting current interventions and strategies that could be enhanced through AI efficiencies. We conclude with a section on the risks and ethical concerns that must be a part of any discussion about AI within public health. This is not intended to be a systematic review covering all interventions that could be enhanced through AI, but rather, a qualitative exploration of the potential for AI to provide innovative solutions and efficiencies for HIV prevention interventions.

PUBLIC HEALTH PRINCIPLES AND US CDC'S HIV INTERVENTIONS AND ACTIVITIES

To identify key areas for improving HIV prevention, our review highlights four key Public Health Principles central to addressing the HIV Epidemic: I) Surveillance and Population Monitoring, II) Case Detection, III) Systematic Treatment and Case Management, and IV) Interruption of Transmission [22, 23]. After briefly describing these public health functions using the US CDC's HIV interventions and activities as examples, we consider ways in which AI may already be, or could be, enhancing HIV interventions within these public health approaches.

(I) Surveillance and Population-based Monitoring

Monitoring HIV (HIV surveillance) is a unique public health function. The US CDC collects and utilizes data from multiple sources, including public health departments and laboratories, healthcare systems, and population surveys, to gain a comprehensive understanding of HIV incidence, prevalence, and epidemiological characteristics [24]. National HIV data systems, such as the *National HIV Surveillance System (NHSS)* [25] and the *Medical Monitoring Project (MMP)* [26], provide representative data for the United States while periodic *Population-based HIV Impact Assessments (PHIAs)* do so for some PEPFAR countries [27]. These systems give crucial insights into the need for and effectiveness of HIV prevention and treatment initiatives nationally and globally. These surveillance data inform program development, policy-making, and resource allocation across the United States and globally as well as the tracking of key indicators and identification of populations and locations in need of focused interventions [24].

(II) Case Detection

The first step in the HIV Care Continuum is diagnosing HIV and ensuring that people with HIV (PWH) are aware of their status [28]. In 2022, an estimated 1.2 million people in the United States were living with HIV, but only 87% knew their HIV status [29]. Globally, even though several countries are reaching the Joint United Nations Programme on HIV and AIDS (UNAIDS) target of 95% of PWH knowing their HIV status, gaps remain, particularly among people most at risk for new infections, including men who have sex with men, sex workers, and people who inject drugs [30]. The US CDC funds HIV testing in state and local health departments, clinics, and community-based organizations throughout the United States as well as PEPFAR countries [31, 32]. The US CDC also supports special initiatives like *Together TakeMeHome* [33], which distributes free HIV self-tests through mail orders. To raise HIV awareness, social marketing campaigns directed at both consumers and providers [34], such as the *Let's Stop HIV Together* [35] campaign, play an important role in enhancing community discussion, reducing stigma, and promoting HIV testing and prevention.

(III) Systematic Treatment and Case Management.

The most recent US CDC surveillance data indicate that in 2022, 24% of people with diagnosed HIV in the United States were not linked to HIV care, and 46% of those with diagnosed HIV were not retained in care [29]. The importance of high-quality linkages to HIV care and treatment services is well established in global settings and core technical consideration for PEPFAR programming [32, 36]. Linking to, engaging in, and being retained in HIV care are important so that PWH are virally suppressed [37]. This not only improves the individual health of PWH but also prevents the onward transmission of HIV to partners, a concept known as *Undetectable=Untransmittable [U=U]* [38], or *Treatment as Prevention [TasP]* [39]. Evidence-based public health strategies such as *Data to Care* [40], which use surveillance data, pharmacy records, clinic appointments, and other data sources to identify PWH not currently receiving care, are effective at locating and returning PWH to care in the United States, while multi-month dispensing of antiretroviral therapy (ART) [41, 42] is shown to be effective in improving viral suppression in non-US settings. Providing

‘whole person care’ and addressing social determinants of health that negatively impact patients’ ability to stay in care, can also enhance retention in HIV care [43, 44].

(IV) Interruption of Transmission

Antiretroviral medication was first approved for the prevention of HIV acquisition (pre-exposure prophylaxis or PrEP), by the US Food and Drug Administration in 2012 and has been recommended globally by the WHO since 2015 [45, 46]. In 2023, over 3.5 million people worldwide received PrEP at least once, with more than 75% of them located in the African region [47]. PrEP uptake has been increasing among persons who could benefit from it [47, 48]. However, it still falls short of the target of 10 million PrEP users worldwide and the national goal of 50% coverage in the United States by 2025 [47, 48]. Furthermore, there are persistent disparities in PrEP uptake and access (e.g., lower uptake among people in the Southern United States or among African Americans) [48–51]. Structural changes in PrEP care settings, such as the integration of PrEP into sexual health clinics [52–54] and delivery of PrEP through telehealth services (telePrEP) [55, 56] can improve access to PrEP care while reducing these disparities.

Another public health approach to the prevention of transmission is *HIV Cluster Detection and Response (CDR)*, a way of identifying places or communities where HIV is spreading rapidly [57]. A cluster or outbreak reflects a failure of our care and prevention services. Through collaboration with state and local public health departments and communities, *CDR* provides a framework to effectively guide the implementation of proven prevention strategies for the people who need them most. This is achieved through providing technical assistance, advice, and even direct staffing to support the response [57].

AI APPLICATION TO HIV PREVENTION AND ACTIVITIES

Given the tremendous capabilities that ML, DL, and Gen AI offer, we consider how these technologies could possibly enhance HIV interventions and activities that facilitate these public health functions (Figure). Although there are numerous areas where these AI technologies could make a potentially significant impact, we focus here on key applications that have already demonstrated success in health contexts and emphasize a few critical areas where we anticipate substantial enhancements in the not-too-distant future.

Machine Learning

One of the key strengths of ML is its ability to analyze large, integrated datasets from multiple sources rapidly. In theory, ML could incorporate information from a wide range of sources by using a set of rules and protocols that allow different software applications to communicate with each other. This could help simplify real-time integration of individual-data from collaborating platforms or data sources, helping to create a more complete picture of an individual’s care history or status. Alternatively, ML could combine aggregate data from diverse settings – clinical (e.g., clinics, hospitals) and non-clinical (e.g., pharmacies, outreach programs, syringe service programs) – to provide a more complete picture of total healthcare usages.

After the integration, ML can analyze these data quickly though the speed of analysis depends on computational resources and the complexity of the models used, such as supervised or unsupervised machine learning methods. Our experience indicates that improving conventional public health surveillance systems – for example, through improvements to *NHSS* [25], *MMP* [26], and *PHIAs* [27] – provides better data with which to make public health decisions. ML might help to integrate all sorts of data that can supplement the surveillance data to provide a more holistic and accurate view of HIV dynamics.

Moreover, by incorporating data that were previously collected and comprehensive risk factors (e.g., combination of substance use with risky sexual behaviors, HIV stigmatization), HIV case detection could be enhanced by identifying areas or populations with a higher likelihood of new HIV cases. Enhanced data can improve the strategic distribution of resources, such as where to market HIV self-testing kits through programs like *Together TakeMeHome* [33]. This targeted approach helps prioritize resources and focus interventions on populations with risk factors more effectively. In the context of HIV treatment for PWH, integrating data from EHRs of various medical facilities, including emergency rooms and correctional facilities, could help identify PWH who are not linked to care or have been lost to follow-up. These challenges have not fully been addressed by current data systems, such as those used in *Data to Care* [40]. Moreover, ML algorithms could detect patterns suggesting gaps in care (e.g., missing appointments, irregularities in lab results) and enable healthcare providers to proactively address these issues and improve patient retention in care.

Additionally, ML's predictive capabilities could identify patients likely to be at risk of non-adherence to ART or of comorbidities (e.g., TB). Of course, any patterns identified through ML will need to be carefully validated before assuming causality. However once validated, ML can facilitate the development of personalized interventions in consideration of social determinants of health; these might include tailored counseling or care plans to improve adherence and health outcomes [43, 44].

Although ML offers significant potential in advancing HIV prevention, it is important to be aware of its limitations, particularly the 'garbage in, garbage out' phenomenon [58]. This issue arises when faulty or biased input data – or the absence of key input data related to HIV risk – lead to inaccurate predictions and ineffective interventions [58, 59]. To take extra care to address these biases and mitigate these risks, it is critical to ensure high-quality, unbiased, and diversified data sources that include underrepresented populations [60]. This can be done by using bias detection or implementing fairness-aware ML algorithms [60]. Employing supervised ML methods, which involve training models on data that has been pre-labeled with the correct outcomes when necessary, can enhance model accuracy. Additionally, ongoing evaluation is key to adjusting models and maintaining their effectiveness and quality, with ML/AI methods requiring continuous monitoring of model performance, including accuracy, bias, and adaptability, which differs from traditional analytics or research projects that may focus more on static evaluations of pre-defined metrics. By addressing these factors, ML can be a more reliable and impactful tool in HIV prevention [58, 60].

Deep Learning

Deep Learning could further enhance HIV interventions by automatically and effectively learning complex hierarchical features from unstructured data. Analyzing social media data, for instance, could profoundly impact various aspects of HIV prevention by detecting misinformation or gaps in public knowledge and monitoring public sentiment about HIV prevention. Additionally, by integrating public data, we might identify patterns or associations that help us better recognize who might benefit from prevention interventions like PrEP but might not be apparent through traditional criteria alone. Gaining deeper contextual insights into the factors driving observed changes in people could move beyond merely capturing the ‘what’ to uncovering the ‘why’ behind HIV trends. Unlike traditional statistical methods, which typically require predefined hypotheses and assumptions, DL can autonomously discover complex, non-linear relationships in large, unstructured datasets, potentially revealing new insights that would not be easily identified through traditional methods. This capability is beyond what traditional HIV data systems, such as *NHSS* [25], *MMP* [26], or *PHIAs* [27] might capture, offering valuable real-time surveillance and insights. Applying DL to big real-time user-generated data from multiple social media platforms (e.g., X, Reddit, Instagram) might help us to understand how members of different demographic groups perceive HIV risk or respond to HIV prevention messaging [61–63]. This type of information could enhance public health campaigns like *Let’s Stop HIV Together* [35] by tailoring outreach efforts to be even more culturally appropriate and reducing stigmatization, especially within minoritized communities.

DL could also be used to enhance *CDR* by improving the identification of HIV transmission networks through the integration of syndemic surveillance data (e.g., HIV or hepatitis C incidence, syringe exchange) from not only health departments, but also from emergency departments, pharmacies, and other healthcare sources with regular and social media content [57]. DL can augment the cluster detection process by analyzing complex data patterns, such as correlations between care-seeking behaviors (e.g., increased visits to emergency departments) and social determinants of health (e.g., drug use or housing instability, no syringe service program) in areas where HIV testing might not be routinely conducted.

Although these capabilities hold great potential, it is also important to acknowledge that at present, only some jurisdictions have the capacity for such integration. Many jurisdictions currently lack the infrastructure and personnel required to support such integrations effectively. Until substantial investments are made in building this capacity at the local, state, and county levels, the implementation of ML could be premature, risking inefficiencies or failures in supporting healthcare systems already under strain.

NLP could enhance HIV treatment by analyzing unstructured data in EHRs, such as clinical notes. This could allow for the creation of more nuanced care plans, providing deeper insights into the health status and syndemic factors affecting patients, and the identification of issues such as poor adherence or psychosocial challenges that may not be captured in structured fields. Further, as CV can analyze visual images, it could contribute to the detection of comorbidities. AI-powered *Computer-Aided Detection* systems can quickly and accurately identify radiographic signs of TB, leading to faster diagnosis and treatment initiation [64]. This technology not only reduces the burden on radiologists but also

ensures that TB cases are identified and managed promptly, reducing transmission rates and improving public health outcomes. Finally, CV could improve HIV testing, by automatically and accurately interpreting HIV self-testing kit results and streamlining case reporting and data collection processes.

Additionally, DL's unsupervised learning and simulation of complex decision-making processes could enhance tools like the *HIV Risk Reduction Tool* [65] or *Find Services Locator* [66] by incorporating personalized risk assessments based on user-provided demographic data and behavioral patterns. This would allow syndemic approaches and tailored recommendations, including referrals to additional ancillary services (e.g., STI treatment, substance abuse programs, mental health services) alongside PrEP care [67].

Although integrating syndemic surveillance data from diverse healthcare facilities holds great promise for enhancing HIV interventions, it is crucial to prioritize the privacy and security of health data. Accurate secure data-sharing practices and proper de-identification of EHR data according to Health Insurance Portability and Accountability Act (HIPPA) standards are essential. AI systems must also incorporate robust data protection measures, including encryption techniques for data transmission with secure data-sharing tools and storage, to ensure the security of personally identifiable information (PII), and establish strict access controls to safeguard PII. Moreover, to ensure long-term success, AI systems must be designed for resilience and adaptability. This includes planning for potential disruptions in funding or political shifts, and ensuring that systems remain functional and effective regardless of changes in external support mechanisms.

Generative AI

Generative AI offers significant potential for advancing HIV interventions by rapidly creating and customizing content tailored to specific audiences. For example, Gen AI-powered chatbots could provide real-time support by delivering personalized advice and answering questions about HIV prevention and treatment. Previous research indicates that some individuals may feel more comfortable discussing sensitive topics, such as their sexuality, with AI chatbots compared to human counselors, highlighting the potential for AI to enhance user engagement and the effectiveness of prevention strategies [20].

Additionally, Gen AI could further enhance self-testing by offering automated, 24/7 HIV self-testing services, including personalized HIV risk assessment, and providing tailored information for risk reduction based on individual's input. Utilizing AI-powered chatbots with HIV self-testing kits might enhance perceived user-friendliness and accessibility of self-testing kits, enabling individuals to test more easily and accurately.

Other areas relevant to HIV prevention that Gen AI could enhance include information dashboards or resource hubs, such as *America's HIV Epidemic Analysis Dashboard (AHEAD)* [68], *AtlasPLUS* [69], *HIV Nexus* [70], and *National Prevention Information Network (NPIN)* [71]. Gen AI might enhance these platforms by generating personalized summaries and culturally sensitive communication materials that engage specific communities, thereby encouraging greater use of prevention services. Additionally, Gen AI could support virtual learning community formats like the *National Alliance of State*

and Territorial AIDS Directors (NASTAD) TelePrEP Learning Collaborative [55] by offering tailored information and technical assistance for integrating telePrEP into practices. These AI-driven tools could operate around the clock – with human monitoring and oversight available for support when needed – ensuring continuous access to critical health information, making such services more efficient, responsive, and personalized. These tools could also be tailored to meet global programs' needs with similar aims of ensuring that personalized information is provided directly to clients.

Moreover, Gen AI could support healthcare providers in enhancing PrEP and HIV treatment and management. Clinical decision-making support tools powered by Gen AI could help healthcare providers deliver care with greater confidence [9, 72]. By empowering non-HIV specialists, community pharmacists, or authorized laypersons with Gen AI tools, access to PrEP care could be expanded. These tools could help non-specialists and other providers prescribe PrEP more confidently, ensuring comprehensive, personalized adherence support even in settings with limited access to HIV specialists. This expansion of roles ensures that PrEP initiatives reach a broader population and provide accurate and timely care. For PWH, Gen AI could help care providers recognize symptoms of comorbidities and generate customized educational materials that could address social determinants of health by including non-medical factors affecting health (e.g., socioeconomic status, geographic location). These materials could also be customized to the patient's literacy level, language, and cultural context, thereby reducing stigma and increasing the understanding of the benefits of viral suppression (e.g., *U=U, TasP* [39]).

A key advantage of Gen AI is its ability to continuously refine its capabilities and performance through pre-learning (i.e., doing a big training), post-training, or increasing inference tokens (i.e., letting the models think for longer). By learning from user interactions, AI-powered tools such as chatbots can continually enhance their guidance and support. AI can analyze user interactions to identify common questions and information gaps as well as feedback from clinicians and communities to uncover common themes and actionable insights. To ensure that Gen AI is implemented safely and responsibly, a 'human in the loop' approach is essential, with experts or communities reviewing and validating AI-generated responses. This feedback loop informs future strategies, continuously improves services, and ensures they meet the evolving needs of the public.

However, despite the benefits of learning from user interactions and creating and customizing content, we acknowledge the potential downsides of AI in this area. Gen AI learns from existing data and creates new content based on what it learned. Thus, if these data contain biases, Gen AI might pick up on those biases, reproduce them in its output, unintentionally spread those biases, and potentially harm patients. This is a big concern, especially in terms of HIV prevention, because it can contribute to ongoing discrimination and misunderstanding in communities. Continuous monitoring and evaluation of Gen AI outputs are necessary to identify and correct biases and errors promptly.

ETHICAL CONSIDERATIONS AND OPPORTUNITIES

Ethical and legal issues in the implementation of AI warrant careful consideration. AI tools, such as ChatGPT® (Open AI), Gemini® (DeepMind) and LLaMA® (Meta), demonstrate significant potential for providing accurate and timely information on HIV-related topics. AI could play a crucial role in reducing health disparity by identifying biases and synthesizing sociocultural factors that extend beyond traditional indicators. This enables the identification of individuals with vulnerabilities not typically included in existing criteria. Additionally, AI can tailor messages, facilitating personalized interventions for underserved or highly affected communities [73]. However, implementing AI into public health requires careful consideration, especially in AI applications for HIV interventions as HIV disproportionately affects marginalized populations with experiences of discrimination. Moreover, it is crucial to adopt a cautious and thoughtful approach to AI integration, particularly in settings where infrastructure and personnel may not be prepared for such advancements. This requires careful planning, adequate preparation, and significant infrastructure investments before implementing AI applications. We have briefly touched on ethical considerations above, particularly those related to issues of biases and privacy in the context of ML, DL, and Gen AI. However, it is essential to continuously emphasize the broader ethical concerns and legal challenges including fairness and transparency in decision-making, which are discussed in this section.

Integrating AI into HIV interventions necessitates a simultaneous consideration and rigorous focus on issues of privacy protection, adherence to ethical guidelines, and reducing health disparities [74]. Additionally, it is essential to be aware of the development of potential biases in the information generated by AI that could adversely affect health disparities by overlooking the socio-political context and inclusivity necessary for effective health communication [60, 74]. There is growing concern that AI-powered algorithms in healthcare could reinforce existing biases, potentially worsening disparities, particularly among people who are at increased/higher risk for HIV [73]. An additional limitation for global settings is that most AIs have been primarily trained on vast amounts of English data, making them less proficient in other languages [75]. To make AI a transformative tool for reducing health disparities, appropriate safeguards and controls (e.g., inclusive data collection, community involvement, regulatory oversight) must be implemented to address longstanding inequities in HIV prevention and treatment [74, 76]. AI technologies must be continuously evaluated and refined to ensure that they not only provide accurate information but also reduce health disparities and address broader socio-cultural dimensions of health communication [77]. This can be achieved through regular human oversight, incorporating feedback from diverse stakeholders and communities, and conducting audits to identify and mitigate biases.

The risks of AI hallucinations must also be considered. These instances where AI models generate inaccurate or misleading information by detecting patterns or objects that do not actually exist or are invisible to humans pose a risk to the reliability of AI-enhanced HIV programs. Marginalized populations may be disproportionately affected, as they often face greater challenges in accessing accurate healthcare information and are underrepresented in AI training data, which can lead to misinformed decisions that exacerbate health disparities [78]. To mitigate this risk, rigorous quality control measures, including validation and testing

protocols, must be implemented throughout the development and training of AI systems. Additionally, incorporating human oversight into AI processes along with incorporating regular audits and validation checks allows healthcare professionals to review and verify AI-generated recommendations before application. For example, AI should be tested to ensure it doesn't unfairly target or exclude certain groups, and feedback from the experts and communities should be used to shape the interventions to ensure they are relevant and respectful. Taking these considerations into account, agencies using AI-enhanced processes should consider developing a comprehensive plan that outlines how AI will be safely and responsibly utilized to enhance public health efficiency and outcomes [6, 79].

The evolving legal landscape surrounding health data privacy presents significant challenges, especially with major tech companies becoming involved in AI development partnerships. Hospitals and healthcare providers must address these legal and ethical challenges carefully to protect patient privacy while advancing AI technologies for medical purposes [80]. Comprehensive consent protocols should be in place when needed (e.g., when sharing PII) and before experimental AI technologies are used for research, ensuring individuals are fully informed about how their data will be used. These protocols should be clear, concise, and written in plain language to ensure that individuals can easily understand the implications. Compliance with privacy regulations, along with maintaining rigorous data protection measures and the option for individuals to opt-out, is essential to safeguard patient information and uphold trust in AI applications.

In the meantime, the relationship between health privacy and AI introduces complex challenges. Although individuals theoretically retain control over their health data, AI technologies can potentially undermine health privacy protections. For example, AI models trained on large datasets may unintentionally expose sensitive health information by generating predictions or insights that can be traced back to individuals, even if personal identifiers are removed. Additionally, AI systems used in health apps or wearables may inadvertently share private health data with third parties, such as advertisers or data brokers, without proper consent, creating new avenues for privacy breaches beyond those already associated with current systems like EHRs, which are vulnerable to hacking. Conversely, privacy regulations may restrict the scope and access to private data, which can hinder the advancement of AI in healthcare [81]. Balancing health privacy with AI advancement is complex but essential. Public health partners and healthcare providers must work to achieve this balance by adopting robust privacy measures, such as encryption, de-identification of data, and transparency in data usage policies, while exploring innovative AI solutions. It will likely be important to transparently inform patients that AI is being leveraged as part of their care and to offer them opportunities to 'opt-out' of AI examinations of identifiable data until technologies are proven to provide benefits.

Finally, community engagement is critical to address concerns related to data security and potential biases within AI algorithms. Involving community members in decision-making processes about data usage helps ensure that their concerns are heard and addressed, and that transparent practices are implemented to maintain public trust. AI systems should be designed with input from diverse users or communities to mitigate biases and ensure fair treatment of all individuals. Therefore, there is a strong call for community consultations,

which should be fairly compensated, to create an inclusive approach to AI implementation in health.

Ethical considerations in AI development and deployment – such as addressing potential biases, ensuring fairness, and promoting transparency in decision-making—are crucial for successfully and safely integrating AI in HIV science and programs. Prioritizing ethical concerns, balancing privacy with technological advancement, and engaging communities will help deliver accurate and trustworthy HIV information and care while building and maintaining patient trust and safety.

CONCLUSION

The combined capabilities of ML, DL, and Gen AI have the potential to strengthen HIV care infrastructure by creating more flexible and adaptive systems. These technologies' capabilities offer the potential to improve the monitoring and management of HIV data challenges by quickly and accurately analyzing vast and complex datasets to generate timely, comprehensive health profiles and predict potential HIV risks. Moreover, they could enhance PrEP care and HIV treatment strategies, increase workforce efficiencies, expand PrEP care in nontraditional settings, and streamline response efforts. Ultimately, harnessing the full potential of these advanced technologies could significantly enhance the effectiveness of HIV interventions, lead to greater efficiencies and more equitable health outcomes with a holistic and syndemic approach, and build a more robust framework for addressing both current and emerging HIV challenges.

AI has the potential to transform HIV interventions; nevertheless, humans need to monitor and ensure that biases are minimized, confidentiality and ethical standards are met, and the risks of AI hallucinations are mitigated. It is essential to integrate AI deliberately, thoughtfully, and with community consultation to achieve its great potential benefits, including accelerating the fight against HIV and ultimately ending the epidemic. With careful implementation and ongoing evaluation, AI has the potential to revolutionize HIV prevention and can make a substantial contribution to global efforts to end the HIV epidemic, leading the path to a healthier future for all.

Acknowledgments

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the US Centers for Disease Control and Prevention.

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Examples of Possible HIV Activities Enhanced by AI Core Functions

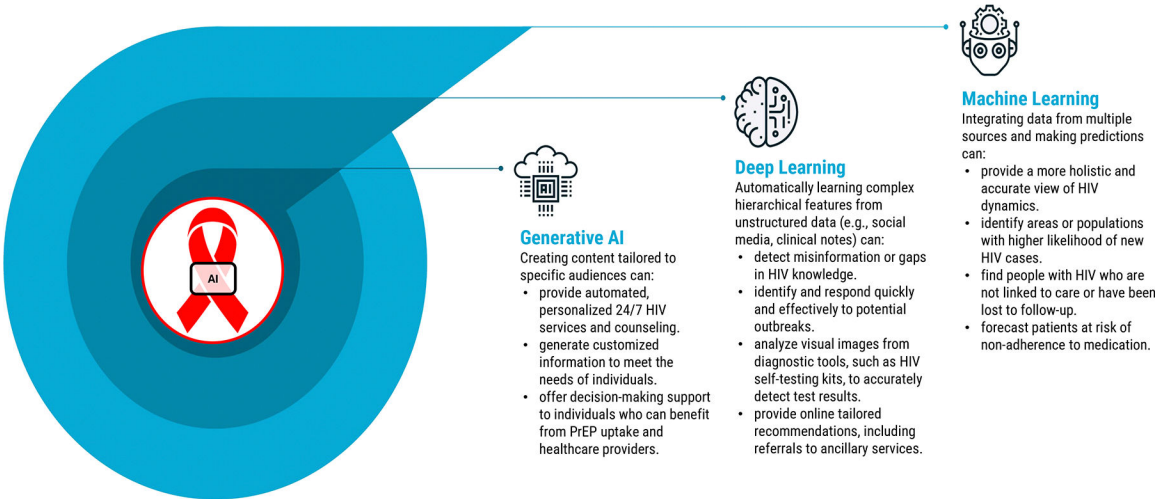


Figure:
Examples of Possible HIV Activities Enhanced by AI Core Functions