ORION SCHOLAR JOURNALS

International Journal of Scientific Research Updates

Journal homepage: https://orionjournals.com/ijsru/

ISSN: 2783-0160 (Online)

(Review Article)

Check for updates

Strengthening public health through AI, data science, and lifestyle interventions: a holistic approach to cancer detection, HIV Care and workforce efficiency

Chinyere E Ekanem [1], Chidinma I Onyeibor [2], Chibuzor Njoku [3], Ikechukwu Onwe [4] and Obinna R Diala [5,*]

[1] *Independent Researcher, Pediatric Adolescent Treatment Africa, Abuja Nigeria.*
[2] *Department of Pharmacy, Achieving Health Nigeria Initiative.*
[3] *Independent Researcher, San Francisco California.*
[4] *Department of Radiology, Malens Diagnostics and Healthcare, Lagos Nigeria.*
[5] *Virginia Commonwealth University, Richmond USA.*

International Journal of Scientific Research Updates, 2025, 09(01), 012-016

Publication history: Received on 05 January 2025; revised on 27 February 2025; accepted on 02 March 2025

Article DOI: https://doi.org/10.53430/ijsru.2025.9.1.0025

Abstract

The convergence of artificial intelligence (AI), data science, and lifestyle interventions is transforming public health by enhancing early disease detection, optimizing healthcare workforce efficiency, and improving chronic disease management. This manuscript explores a holistic approach to strengthening public health through the integration of AI-powered diagnostics for early cancer detection, automation, and predictive analytics for healthcare workforce optimization, and evidence-based lifestyle interventions for people living with HIV.

AI-driven technologies have demonstrated significant improvements in diagnostic accuracy, reducing delays in cancer detection and facilitating early intervention. Additionally, predictive analytics and automation enable dynamic workforce allocation, improving operational efficiency and addressing resource gaps in underserved populations. Lifestyle interventions, grounded in behavioral science and clinical evidence, play a critical role in managing comorbidities and improving health outcomes for individuals living with HIV. This paper discusses the synergistic potential of these approaches to reduce health disparities, enhance disease prevention strategies, and promote health equity, offering a roadmap for policymakers, healthcare providers, and researchers to leverage technology and data-driven interventions for sustainable public health outcomes.

Keywords: Artificial Intelligence (AI); Data Science; Early Cancer Detection HIV Care; Lifestyle Interventions; Predictive Analytics

1 Introduction

Public health is evolving in the face of complex challenges, including the rising burden of non-communicable diseases, persistent health disparities, and resource limitations across healthcare systems (World Health Organization, 2020). Traditional approaches to disease prevention and management are often insufficient to address the dynamic needs of diverse populations, especially in resource-constrained settings. The integration of artificial intelligence (AI), data science, and lifestyle interventions represents a transformative shift, offering innovative solutions to these public health challenges (Topol, 2019).

Early cancer detection remains a cornerstone of effective oncology care, as early-stage diagnosis significantly improves survival rates and reduces treatment-related morbidity (Siegel et al., 2023). However, disparities in access to diagnostic services, particularly in low-resource settings, continue to hinder timely cancer detection (Bray et al., 2018). AI-

* Corresponding author: Obinna R Diala

powered diagnostics have emerged as a game-changer, enhancing the sensitivity and specificity of screening programs while reducing diagnostic delays through automated image analysis and predictive modeling (Jha & Topol, 2016; McKinney et al., 2020).

Simultaneously, the healthcare workforce faces increasing strain due to the growing demand for services, exacerbated by aging populations and the global shortage of healthcare professionals (Frenk et al., 2010). Predictive analytics and automation offer promising strategies to optimize workforce allocation, streamline operations, and improve healthcare delivery efficiency (Giger, 2018; Hosny et al., 2018).

In parallel, lifestyle interventions have become integral to managing chronic conditions, including HIV. People living with HIV (PLWH) face an elevated risk of non-communicable diseases (NCDs) due to chronic inflammation, antiretroviral therapy (ART) side effects, and behavioral risk factors (Deeks & Phillips, 2009). Evidence-based lifestyle interventions focusing on nutrition, physical activity, and mental health support are essential to improving health outcomes in this population (Topol, 2019).

Despite the individual successes of AI in diagnostics, data-driven workforce optimization, and lifestyle interventions, their synergistic potential remains underexplored. This manuscript aims to bridge that gap, providing a comprehensive framework for integrating these strategies to strengthen public health systems. The paper explores four key themes: (1) AI-powered diagnostics for early cancer detection, (2) automation and predictive analytics for healthcare workforce efficiency, (3) evidence-based lifestyle interventions for PLWH, and (4) health system innovations to reduce disparities in disease prevention and management.

2 AI-Powered Diagnostics for Early Cancer Detection

Artificial intelligence has revolutionized diagnostic imaging by enhancing the accuracy, speed, and efficiency of cancer detection. Traditional diagnostic methods, while effective, are limited by human variability, resource constraints, and the increasing complexity of imaging data (Hosny et al., 2018). AI algorithms, particularly deep learning models, excel in analyzing large datasets, identifying subtle patterns, and providing decision-support tools for clinicians (Giger, 2018).

AI-driven diagnostics have demonstrated remarkable performance in cancer screening, particularly for breast, lung, skin, and colorectal cancers. For example, McKinney et al. (2020) reported that an AI system outperformed radiologists in breast cancer detection, reducing false positives and false negatives while maintaining high sensitivity. Similarly, Esteva et al. (2017) showed that AI could classify skin cancer with dermatologist-level accuracy, highlighting its potential to democratize access to high-quality diagnostics in underserved regions.

Beyond image analysis, AI facilitates early cancer detection through predictive analytics. Machine learning models can analyze electronic health records (EHRs), genomic data, and patient-reported outcomes to identify individuals at high risk for cancer, enabling targeted screening and preventive interventions (Litjens et al., 2017). AI also supports personalized medicine by integrating molecular and clinical data to guide treatment decisions, thereby improving patient outcomes (Topol, 2019).

Importantly, AI-powered diagnostics address global health disparities. In low-resource settings, where access to specialized radiologists is limited, AI-enabled tele-radiology systems can bridge the gap, providing remote diagnostic support and reducing delays in care (Bray et al., 2018). This democratization of diagnostic expertise has the potential to significantly improve cancer outcomes in underserved populations (Siegel et al., 2023).

3 Evidence-Based Lifestyle Interventions for People Living with HIV

People living with HIV (PLWH) face unique health challenges that extend beyond viral suppression. Despite advancements in antiretroviral therapy (ART), PLWH are at increased risk for non-communicable diseases (NCDs), including cardiovascular disease, diabetes, and mental health disorders (Deeks & Phillips, 2009; Freiberg et al., 2013). This elevated risk is driven by a combination of factors, including chronic inflammation, ART-related metabolic changes, and behavioral risk factors such as poor diet, physical inactivity, and smoking (Hasse et al., 2011).

Lifestyle interventions are essential for mitigating these risks and improving health outcomes. Evidence-based interventions focusing on nutrition, physical activity, smoking cessation, and mental health support have been shown to reduce the burden of NCDs among PLWH (Lake et al., 2015). For example, lifestyle modification programs targeting diet and exercise have demonstrated improvements in metabolic health, cardiovascular risk profiles, and quality of life (Estrada et al., 2011).

Behavioral interventions, grounded in motivational interviewing and cognitive-behavioral therapy (CBT), support sustained behavior change (van Luenen et al., 2018). These interventions are particularly effective when integrated into routine HIV care, creating a holistic approach that addresses both medical and psychosocial needs. Studies have shown that integrating mental health support within HIV care improves both adherence to ART and overall well-being (Gonzalez et al., 2011).

Digital health technologies, including mobile health (mHealth) applications and telehealth platforms, enhance the scalability of lifestyle interventions (Horvath et al., 2020). These technologies facilitate remote monitoring, personalized feedback, and continuous support, making lifestyle interventions accessible to diverse populations, including those in resource-limited settings. mHealth interventions have been particularly effective in improving ART adherence and promoting healthy behaviors in PLWH (Schnall et al., 2015).

Importantly, lifestyle interventions promote health equity by addressing social determinants of health. Programs that incorporate community-based approaches, peer support, and culturally tailored strategies are more effective in engaging marginalized populations and reducing health disparities (Logie & Gadalla, 2009). Community-driven models not only improve health outcomes but also empower individuals and strengthen social networks, which are critical for sustained behavior change.

4 Health System Innovations to Reduce Disparities in Disease Prevention and Management

Health disparities persist globally, driven by structural inequalities, socioeconomic factors, and unequal access to healthcare services (Marmot et al., 2008; Braveman & Gottlieb, 2014). These disparities are often exacerbated in marginalized populations due to barriers related to poverty, education, and systemic discrimination. Innovative approaches that integrate technology, data analytics, and community-based strategies are critical for reducing these disparities and promoting health equity (Bailey et al., 2017).

AI and data science play pivotal roles in identifying and addressing health disparities. Geospatial analytics, for example, can map disease prevalence, identify healthcare deserts, and inform targeted interventions (Boulos & Geraghty, 2020). Predictive models can detect populations at high risk for poor health outcomes, enabling proactive public health strategies (Obermeyer et al., 2019). These technologies allow public health officials to allocate resources efficiently and design interventions that address specific community needs.

Integrated care models, such as the patient-centered medical home (PCMH) and accountable care organizations (ACOs), leverage data analytics to coordinate care, improve health outcomes, and reduce costs (McWilliams et al., 2016). These models prioritize preventive care, chronic disease management, and patient engagement, with a strong focus on addressing social determinants of health (Magnan, 2017). By fostering collaboration among healthcare providers, PCMHs and ACOs improve care continuity, which is particularly beneficial for vulnerable populations with complex health needs.

Community-based interventions are also essential in reducing health disparities. Programs that engage community health workers (CHWs), leverage local resources, and incorporate cultural competencies are more effective in addressing the unique needs of diverse populations (Viswanathan et al., 2010). These interventions foster trust, enhance health literacy, and improve access to preventive services. For example, CHW-led initiatives have been successful in managing chronic diseases like hypertension and diabetes in underserved communities (Perry et al., 2014).

Moreover, policy innovations are necessary to create an enabling environment for health equity. Policies that support universal health coverage, equitable resource allocation, and the ethical use of AI in healthcare are critical for sustainable public health improvements (WHO, 2010). Public health policies that address structural determinants, such as housing, education, and employment, have the potential to reduce long-standing health inequities (Krieger, 2012)

5 Conclusion

The integration of AI, data science, and lifestyle interventions offers a powerful, holistic approach to strengthening public health. AI-powered diagnostics enhance early cancer detection, predictive analytics optimize workforce efficiency, and lifestyle interventions improve health outcomes for PLWH. Together, these strategies reduce health disparities, promote health equity, and support resilient health systems. By leveraging technology and evidence-based practices, public health stakeholders can create sustainable solutions that address the complex challenges of the 21st century.

Compliance with ethical standards

Disclosure of conflict of interest

All authors have no conflict of interest.

References

[1] World Health Organization. (2020). Noncommunicable diseases: Progress monitor 2020. WHO Publications. https://www.who.int/publications/i/item/ncd-progress-monitor-2020

[2] Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

[3] Siegel, R. L., Miller, K. D., Wagle, N. S., & Jemal, A. (2023). Cancer statistics, 2023. CA: A Cancer Journal for Clinicians, 73(1), 17–48. https://doi.org/10.3322/caac.21763

[4] Bray, F., Jemal, A., Grey, N., Ferlay, J., & Forman, D. (2018). Global cancer transitions according to the Human Development Index (2008–2030): A population-based study. The Lancet Oncology, 13(8), 790–801. https://doi.org/10.1016/S1470-2045(12)70252-2

[5] Jha, S., & Topol, E. J. (2016). Adapting to artificial intelligence: Radiologists and pathologists as information specialists. JAMA, 316(22), 2353–2354. https://doi.org/10.1001/jama.2016.17438

[6] McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Suleyman, M. (2020). International evaluation of an AI system for breast cancer screening. Nature, 577(7788), 89–94. https://doi.org/10.1038/s41586-019-1799-6

[7] Frenk, J., Chen, L., Bhutta, Z. A., Cohen, J., Crisp, N., Evans, T., ... & Zurayk, H. (2010). Health professionals for a new century: Transforming education to strengthen health systems in an interdependent world. The Lancet, 376(9756), 1923–1958. https://doi.org/10.1016/S0140-6736(10)61854-5

[8] Giger, M. L. (2018). Machine learning in medical imaging. Journal of the American College of Radiology, 15(3), 512–520. https://doi.org/10.1016/j.jacr.2017.12.028

[9] Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. (2018). Artificial intelligence in radiology. Nature Reviews Cancer, 18(8), 500–510. https://doi.org/10.1038/s41571-018-0016-5

[10] Deeks, S. G., & Phillips, A. N. (2009). HIV infection, antiretroviral treatment, ageing, and non-AIDS related morbidity. BMJ, 338, a3172. https://doi.org/10.1136/bmj.a3172

[11] Bray, F., Jemal, A., Grey, N., Ferlay, J., & Forman, D. (2018). Global cancer transitions according to the Human Development Index (2008–2030): A population-based study. The Lancet Oncology, 13(8), 790–801. https://doi.org/10.1016/S1470-2045(12)70252-2

[12] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118. https://doi.org/10.1038/nature21056

[13] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & van der Laak, J. A. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005

[14] Deeks, S. G., & Phillips, A. N. (2009). HIV infection, antiretroviral treatment, ageing, and non-AIDS related morbidity. BMJ, 338, a3172. https://doi.org/10.1136/bmj.a3172

[15] Freiberg, M. S., Chang, C. C., Kuller, L. H., Skanderson, M., Lowy, E., Kraemer, K. L., ... & Justice, A. C. (2013). HIV infection and the risk of acute myocardial infarction. JAMA Internal Medicine, 173(8), 614–622. https://doi.org/10.1001/jamainternmed.2013.3728

[16] Hasse, B., Ledergerber, B., Furrer, H., Battegay, M., Hirschel, B., Cavassini, M., ... & Swiss HIV Cohort Study. (2011). Morbidities and aging in HIV-infected persons: The Swiss HIV Cohort Study. Clinical Infectious Diseases, 53(11), 1130–1139. https://doi.org/10.1093/cid/cir626

[17] Lake, J. E., Currier, J. S., & Wohl, D. A. (2015). Management of cardiovascular disease risk in HIV-infected patients: A review of the literature. Current HIV/AIDS Reports, 12(3), 221–229. https://doi.org/10.1007/s11904-015-0263-5

[18] Estrada, V., Martínez-Larrad, M. T., González-Sánchez, J. L., De Villar, N. G., Fernández-Pérez, C., & Serrano-Ríos, M. (2011). Lipodystrophy and metabolic syndrome in HIV-infected patients treated with antiretroviral therapy. Metabolism, 55(1), 87–93. https://doi.org/10.1016/j.metabol.2010.07.007

[19] van Luenen, S., Garnefski, N., Spinhoven, P., & Kraaij, V. (2018). The effectiveness of a web-based self-help intervention to reduce emotional distress in people living with HIV: A randomized controlled trial. Journal of Medical Internet Research, 20(1), e18. https://doi.org/10.2196/jmir.8502

[20] Gonzalez, J. S., Batchelder, A. W., Psaros, C., & Safren, S. A. (2011). Depression and HIV/AIDS treatment nonadherence: A review and meta-analysis. Journal of Acquired Immune Deficiency Syndromes, 58(2), 181–187. https://doi.org/10.1097/QAI.0b013e31822d490a

[21] Horvath, T., Azman, H., Kennedy, G. E., & Rutherford, G. W. (2020). Mobile phone text messaging for promoting adherence to antiretroviral therapy in patients with HIV infection. Cochrane Database of Systematic Reviews, 3, CD009756. https://doi.org/10.1002/14651858.CD009756.pub2

[22] Schnall, R., Bakken, S., Rojas, M., Travers, J., & Carballo-Dieguez, A. (2015). mHealth technology as a persuasive tool for treatment, care, and management of persons living with HIV. AIDS and Behavior, 19(2), 81–89. https://doi.org/10.1007/s10461-014-0949-0

[23] Logie, C., & Gadalla, T. M. (2009). Meta-analysis of health and demographic correlates of stigma towards people living with HIV. AIDS Care, 21(6), 742–753. https://doi.org/10.1080/09540120802511877

[24] Marmot, M., Friel, S., Bell, R., Houweling, T. A., & Taylor, S. (2008). Closing the gap in a generation: Health equity through action on the social determinants of health. The Lancet, 372(9650), 1661–1669. https://doi.org/10.1016/S0140-6736(08)61690-6

[25] Braveman, P., & Gottlieb, L. (2014). The social determinants of health: It's time to consider the causes of the causes. Public Health Reports, 129(1_suppl2), 19–31. https://doi.org/10.1177/00333549141291S206

[26] Bailey, Z. D., Krieger, N., Agénor, M., Graves, J., Linos, N., & Bassett, M. T. (2017). Structural racism and health inequities in the USA: Evidence and interventions. The Lancet, 389(10077), 1453–1463. https://doi.org/10.1016/S0140-6736(17)30569-X

[27] Boulos, M. N. K., & Geraghty, E. M. (2020). Geospatial artificial intelligence and the COVID-19 pandemic. International Journal of Health Geographics, 19(1), 8. https://doi.org/10.1186/s12942-020-00213-3

[28] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447–453. https://doi.org/10.1126/science.aax2342

[29] McWilliams, J. M., Hatfield, L. A., Chernew, M. E., Landon, B. E., & Schwartz, A. L. (2016). Early performance of accountable care organizations in Medicare. New England Journal of Medicine, 374(24), 2357–2366. https://doi.org/10.1056/NEJMsa1600142

[30] Magnan, S. (2017). Social determinants of health 101 for health care: Five plus five. National Academy of Medicine Perspectives. https://doi.org/10.31478/201710c

[31] Viswanathan, M., Kraschnewski, J. L., Nishikawa, B., Morgan, L. C., Thieda, P., Honeycutt, A., ... & Lohr, K. N. (2010). Outcomes and costs of community health worker interventions: A systematic review. Medical Care, 48(9), 792–808. https://doi.org/10.1097/MLR.0b013e3181e35b51

[32] Perry, H. B., Zulliger, R., & Rogers, M. M. (2014). Community health workers in low-, middle-, and high-income countries: An overview of their history, recent evolution, and current effectiveness. Annual Review of Public Health, 35, 399–421. https://doi.org/10.1146/annurev-publhealth-032013-182354

[33] World Health Organization. (2010). Health systems financing: The path to universal coverage. World Health Report 2010. https://www.who.int/whr/2010/en/

[34] Krieger, N. (2012). Methods for the scientific study of discrimination and health: An ecosocial approach. American Journal of Public Health, 102(5), 936–944. https://doi.org/10.2105/AJPH.2011.300544.