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Review

AI-driven Disease Prevention with a Special Emphasis on Respiratory Diseases and Pulmonary Public Health

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Abstract

Artificial intelligence (AI) is increasingly transforming systems biology and preventive medicine by enabling the integration of multidimensional molecular, clinical, environmental, and population-level data to model complex biological networks underlying health and disease. In respiratory medicine, AI-driven network approaches have demonstrated significant potential for improving disease classification, biomarker discovery, and risk stratification in conditions such as chronic obstructive pulmonary disease (COPD), asthma, pulmonary fibrosis, and emerging respiratory infections. Integrated disease prevention in this context requires the convergence of molecular mechanisms, epidemiological insights, and public health strategies to address both individual susceptibility and population-level risk. AI-based frameworks facilitate the analysis of high-dimensional respiratory datasets, enhance disease surveillance and outbreak detection, support predictive modeling of environmental and lifestyle exposures (e.g., air pollution and smoking), and improve clinical decision-making and health communication. Despite these advances, substantial challenges remain, including data heterogeneity, algorithmic bias, privacy and ethical concerns, and unequal access to digital technologies, particularly in low- and middle-income countries. Addressing these limitations through ethical governance, context-specific AI model development, and capacity building is essential for advancing equitable, sustainable, and effective respiratory disease prevention and public health systems.

Keywords

Artificial intelligence, Respiratory disease prevention, Systems biology, Public health informatics, Disease surveillance, Ethical governance

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1. Introduction

Disease prevention has evolved from a narrowly defined biomedical paradigm—primarily focused on individual pathogens and isolated risk factors—toward a more integrative framework that recognizes the complex interplay among biological, behavioral, environmental, and social determinants of health [1,2]. The contemporary global burden of disease, particularly noncommunicable diseases (NCDs) such as cardiovascular disorders, diabetes, cancer, and chronic respiratory diseases, alongside emerging and re-emerging infectious diseases, cannot be effectively addressed through fragmented interventions [3-5]. Instead, sustainable disease prevention requires coordinated strategies that integrate molecular mechanisms, population-level epidemiological evidence, and public health action. Comprehensive disease prevention refers to approaches that synthesize insights from molecular biology (including genetics and epigenetics), epidemiology, behavioral sciences, environmental health, and health policy to reduce disease risk across the lifespan. This integrative perspective aligns with systems thinking in health, which conceptualizes disease as the outcome of dynamic interactions between individuals and their environments [6,7]. Such an approach is particularly relevant for respiratory diseases, where genetic susceptibility, environmental exposures (e.g., air pollution and tobacco smoke), infectious agents, and socioeconomic factors jointly shape disease onset and progression. Despite advances in molecular diagnostics and public health strategies, several critical challenges remain in respiratory disease prevention, including the integration of heterogeneous data sources, limited capacity to model complex gene–environment interactions, delayed risk identification, and insufficient linkage between individual-level and population-level health data. These limitations highlight the need for advanced analytical frameworks, such as artificial intelligence (AI), capable of addressing the complexity and scale of modern respiratory health challenges. This review critically examines the molecular foundations, epidemiological evidence, and public health implications of comprehensive disease prevention, emphasizing their relevance to modern healthcare systems and future research directions [8].

Prevention and control represent complementary yet distinct strategies in disease management. While control efforts are typically implemented once disease is established, preventive strategies aim to reduce risk before irreversible damage occurs. In practice, however, control measures are often initiated late in the disease course, particularly in chronic conditions such as respiratory diseases, where structural and functional damage may already be advanced [9,10]. Achieving an optimal balance between prevention and control remains a persistent challenge, particularly as healthcare systems attempt to incorporate advanced molecular and digital technologies into routine practice [11-13]. AI has emerged as a transformative tool in this context, enabling the integration and interpretation of complex, high-dimensional biological and clinical datasets. Machine learning (ML) and deep learning techniques are increasingly applied to multi-omics data—including genomics, transcriptomics, proteomics, and metabolomics—to identify clinically relevant patterns, support biomarker discovery, and enhance disease classification and risk prediction [14,15]. In respiratory medicine, these approaches have demonstrated growing utility in predicting disease progression, stratifying patient risk, and supporting precision diagnostics across both chronic and infectious pulmonary conditions [16]. AI also enhances the performance of biomolecular sensors by optimizing signal processing and enabling near real-time diagnostic interpretation [10,17]. Despite these advances, challenges related to data quality, model interpretability, regulatory oversight, and standardization remain. Ongoing developments in explainable AI, data integration frameworks, and validation strategies are expected to further strengthen the clinical applicability of AI in molecular diagnostics and precision medicine [18-20].

Parallel advances in molecular technologies are further transforming disease detection and prevention. High-throughput sequencing, rapid pathogen identification, and genomic surveillance systems have significantly improved the ability to detect infectious agents, characterize transmission dynamics, and inform targeted interventions [21,22]. These developments are particularly critical in respiratory infections, where timely diagnosis and surveillance are essential for outbreak preparedness and response. The increasing availability of point-of-care molecular diagnostics, especially in resource-limited settings, also offers opportunities to reduce disparities in access to precision healthcare [23]. Moreover, advances in bioinformatics and curated molecular databases now enable rapid comparison and analysis of pathogen genomes, supporting real-time epidemiological insights and evidence-based decision-making [24,25]. Collectively, these developments position AI-enabled molecular and epidemiological integration as a central pillar of next-generation disease prevention, with particular relevance to respiratory health and global public health resilience. This review aims to provide a comprehensive and integrative analysis of AI-driven disease prevention, with a particular focus on respiratory diseases and pulmonary public health. Specifically, it synthesizes current evidence across three interconnected domains: (i) molecular mechanisms, including epigenetic regulation and multi-omics integration; (ii) disease classification and predictive modeling using AI-based approaches; and (iii) epidemiological and public health applications, including surveillance, behavioral interventions, and policy frameworks. Unlike previous reviews that address these areas in isolation, this work adopts a systems-level perspective to bridge molecular biology, epidemiology, and public health through AI. In doing so, the review also identifies key knowledge gaps, including challenges related to data heterogeneity, model interpretability, clinical translation, and equity in AI deployment, and highlights future research directions for developing more integrated, ethical, and effective disease prevention strategies.

2. Role of AI in the Conceptual Foundations of Integrative Molecular Disease Prevention

Traditional models of disease causation, such as germ theory and single-risk factor frameworks, have contributed substantially to public health advances but are insufficient for addressing the complex etiology of chronic and environmentally driven respiratory diseases. Conditions such as chronic obstructive pulmonary disease (COPD), asthma, interstitial lung disease, lung cancer, and emerging respiratory infections arise from multifactorial interactions involving genetic susceptibility, epigenetic regulation, environmental exposures, lifestyle behaviors, and social determinants of health. Consequently, effective prevention of respiratory diseases requires integrative, systems-based approaches that extend beyond isolated biological or clinical factors [26,27].

AI has emerged as a foundational tool in this paradigm by enabling the integration and analysis of high-dimensional biological, environmental, and population-level data relevant to pulmonary health. At the molecular level, respiratory disease susceptibility and progression are shaped by interactions among genomic variation, epigenetic modifications, airway microbiota, metabolic signaling, immune regulation, and environmental exposures such as air pollution, occupational hazards, and tobacco smoke. These interactions are inherently complex and nonlinear, limiting the utility of traditional analytical methods. AI-based models provide the computational capacity to integrate these multidimensional datasets and to identify early molecular and physiological markers predictive of respiratory disease risk, exacerbations, and long-term outcomes [28,29].

The conceptual framework of AI-driven respiratory disease prevention is anchored in three complementary pillars: the social determinants of health, the life-course approach, and systems biology. Social and environmental determinants–including air quality, housing conditions, occupational exposures, socioeconomic status, and access to healthcare–play a central role in shaping pulmonary health and respiratory disease burden. The life-course perspective highlights that early-life exposures, including prenatal and childhood air pollution, respiratory infections, and nutritional status, can induce lasting molecular and structural changes in the lung that predispose individuals to chronic respiratory disease later in life. Systems biology and network medicine further demonstrate that respiratory pathophysiology arises from coordinated dysregulation of interconnected molecular and cellular networks rather than isolated pathways. Together, these perspectives establish a robust conceptual basis for AI-enabled prevention strategies that address both upstream determinants and downstream molecular mechanisms of respiratory disease [30].

Within this framework, AI facilitates a transition from reactive management of respiratory conditions toward predictive and preventive pulmonary healthcare. ML models enable early risk stratification for diseases such as COPD, asthma, and lung cancer by integrating molecular biomarkers, imaging features, environmental exposure data, and clinical histories [31-33]. AI-driven predictive modeling can anticipate disease progression, identify individuals at high risk of acute exacerbations, and evaluate the potential impact of preventive interventions–such as pollution reduction, smoking cessation, or targeted screening–before irreversible lung damage occurs [26].

Moreover, AI serves as a critical integrative bridge between molecular diagnostics, respiratory imaging, digital health platforms, and real-world data sources. This integration enhances respiratory disease surveillance, supports evidence-based pulmonary public health decision-making, and aligns with the Prevention, Personalization, and Participation (P4) model of healthcare. In the context of respiratory health, AI-driven platforms enable continuous monitoring of lung function, environmental exposures, and symptom patterns, facilitating early intervention and patient engagement. At the population level, AI strengthens pulmonary public health systems by improving outbreak detection for respiratory infections, optimizing resource allocation, and supporting precision prevention strategies tailored to vulnerable populations [16,34]. Overall, AI functions as a unifying conceptual framework linking molecular biology, respiratory systems medicine, and pulmonary public health. By enabling predictive modeling, multidimensional data integration, and early risk identification, AI-driven approaches support the evolution of respiratory healthcare toward predictive, preventive, and personalized medicine. This paradigm is essential for reducing the global burden of respiratory diseases and advancing sustainable, data-driven pulmonary public health strategies.

3. AI Perspectives on the Molecular Mechanisms of Comprehensive Disease Prevention

3.1 Epigenetics and Gene-Environment Interactions in Respiratory Disease Prevention

Epigenetics provides one of the most compelling molecular frameworks for comprehensive disease prevention by explaining heritable and reversible changes in gene expression that occur without alterations to the underlying DNA sequence. Core epigenetic mechanisms–including DNA methylation, histone modifications, and non-coding RNA-mediated regulation-serve as critical molecular interfaces linking environmental exposures to genetic susceptibility. These mechanisms are particularly relevant to respiratory diseases, where long-term exposure to air pollutants, tobacco smoke, occupational toxins, allergens, and psychosocial stressors can induce persistent epigenetic reprogramming in airway epithelial and immune cells.

AI, particularly ML, is increasingly applied to epigenetic data integration and interpretation, offering new opportunities to address challenges in disease prevention and early diagnosis. AI-driven epigenomic analyses have demonstrated utility in improving diagnostic accuracy, identifying prognostic biomarkers, and elucidating disease mechanisms, especially in conditions characterized by complex gene-environment interactions. However, beyond these applications, the principal strength of AI lies in its capacity to model the nonlinear, high-order interactions between environmental exposures and epigenetic regulation that cannot be captured using traditional statistical approaches.

Gene-environment interactions in respiratory diseases are inherently multidimensional and nonlinear, involving feedback loops between environmental exposures (e.g., air pollution), epigenetic modifications, immune responses, and tissue remodeling. Conventional regression-based models often assume linearity and independence among variables, thereby oversimplifying these relationships. In contrast, AI models particularly deep learning, Bayesian networks, and ensemble learning methods enable the identification of complex interaction patterns, hierarchical dependencies, and latent variables across multi-layered datasets. For example, studies integrating multi-omics and environmental exposure data have shown that AI can uncover combinatorial effects of pollutants and DNA methylation signatures that are not detectable through single-variable analyses [12,35,36]. While these approaches have been widely explored in cancer and cardiovascular diseases, their application to rare disorders and chronic respiratory diseases remains comparatively underdeveloped [37,38]. Importantly, existing studies show both convergence and variability in findings: while many consistently report associations between air pollution exposure and altered DNA methylation in inflammation-related genes, discrepancies exist regarding the specific loci and directionality of methylation changes, likely due to differences in population structure, exposure assessment, and analytical methods. AI-based integrative frameworks have been proposed as a solution to reconcile these inconsistencies by harmonizing heterogeneous datasets and identifying reproducible molecular signatures across studies.

Adapting AI strategies successfully implemented in common diseases may accelerate epigenomic research in underexplored disease domains, including rare pulmonary disorders and environmentally driven respiratory conditions. AI-enabled epigenetic modeling enhances understanding of how airway-specific epigenetic alterations contribute to disease susceptibility, progression, and therapeutic response. Nevertheless, current evidence also highlights limitations: many AI models remain “black-box” systems, limiting biological interpretability, and some studies report reduced generalizability when models are applied across populations with different environmental or genetic backgrounds [39].

Despite major advances in sequencing technologies, a substantial proportion of patients with chronic respiratory and immune-mediated diseases remain without clear molecular diagnoses. Epigenetics has emerged as a powerful framework for bridging this gap, as demonstrated by clinically validated epigenetic biomarkers and epigenetic therapies in oncology and inflammatory diseases. These insights are increasingly relevant to respiratory disorders such as asthma, COPD, and allergic airway diseases, where epigenetic dysregulation contributes to immune imbalance and airway remodeling [40,41].

Traditional analytical approaches are increasingly inadequate for managing the scale and complexity of modern epigenomic data. The rapid expansion of high-resolution epigenetic datasets necessitates the adoption of advanced AI architectures capable of handling multidimensional genomic and proteomic information. ML and deep learning approaches have shown strong performance in disease classification, biomarker discovery, and therapeutic target identification. Nevertheless, the application of AI-based epigenetic frameworks to respiratory disease prevention remains an emerging area, requiring further methodological refinement and high-quality data integration to ensure biological validity [42]. However, a critical synthesis of current literature suggests that predictive performance does not always translate into causal understanding, and there remains a gap between AI-driven pattern recognition and mechanistic interpretation of gene–environment interactions.

Lifestyle and environmental factors including diet, physical activity, tobacco exposure, psychosocial stress, and ambient air pollution are now well recognized as drivers of epigenetic alterations that increase the risk of respiratory, cardiovascular, metabolic, and malignant diseases. Aberrant DNA methylation patterns have been strongly associated with airway inflammation, impaired lung development, and increased susceptibility to chronic respiratory diseases. Importantly, many epigenetic modifications are reversible, positioning them as attractive targets for preventive and therapeutic interventions aimed at reducing long-term pulmonary disease burden [43].

From a preventive perspective, accumulating evidence highlights the importance of early-life and sustained interventions across the lifespan. Epigenetic changes induced during critical developmental windows—such as prenatal exposure to air pollution or early childhood respiratory infections—can persist into adulthood and influence long-term respiratory health. These findings strongly support integrative prevention strategies that combine behavioral modification, environmental protection, and public health policy with molecular-level interventions (Figure 1).

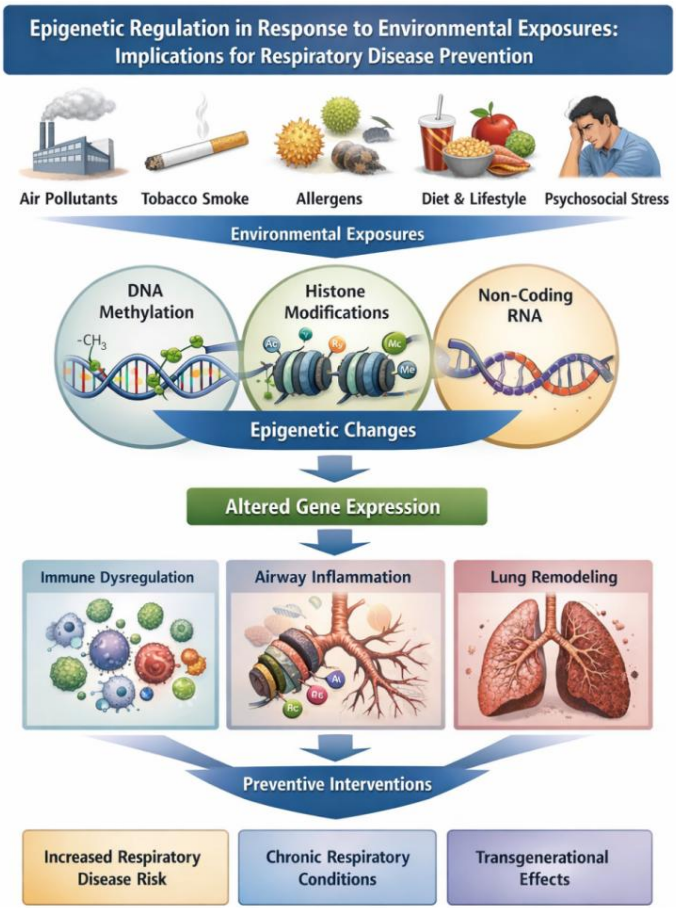

Figure 1. Epigenetic regulation of gene expression in response to environmental exposures and its implications for respiratory disease prevention. This schematic illustrates how environmental exposures—including air pollutants, tobacco smoke, allergens, dietary factors, and psychosocial stress—induce epigenetic modifications such as DNA methylation, histone alterations, and non-coding RNA regulation without changing the DNA sequence. These dynamic and partially reversible molecular changes modulate gene expression programs involved in immune regulation, airway inflammation, and lung remodeling, thereby influencing long-term susceptibility to respiratory and chronic diseases.

Recent studies have further confirmed the role of epigenetic mechanisms in respiratory and allergic diseases [44,45]. Alterations in histone modifications and microRNA regulation have been shown to mediate immune dysregulation in asthma and allergic airway inflammation, influencing disease severity and treatment response. These epigenetic processes may also be transmitted across generations, reinforcing the need for early preventive strategies targeting immune regulation in respiratory diseases [46,47]. Overall, while there is strong consensus that gene-environment interactions mediated through epigenetics are central to respiratory disease pathogenesis, inconsistencies across studies and limited causal inference highlight the need for explainable and integrative AI models capable of bridging molecular mechanisms with population-level exposures. Despite substantial progress, identifying causal epigenetic markers remains challenging, underscoring the need for multiscale, AI-enabled models to clarify the complex relationships linking environment, epigenetics, immune function, and respiratory health outcomes.

3.2 Role of AI in Molecular and Biomedical Data Analysis

AI, encompassing ML and deep learning methodologies, has become essential for analyzing complex molecular and biomedical datasets that exceed the capacity of conventional computational approaches [48]. High-throughput technologies—including next-generation sequencing, multi-omics profiling, and large-scale clinical and environmental data collection—generate vast and heterogeneous datasets requiring advanced analytical frameworks. AI-based algorithms enable robust pattern recognition, disease classification, and outcome prediction, substantially advancing biomedical research and clinical decision-making, particularly in respiratory and immune-mediated diseases [49,50].

3.3 High-Dimensional Omics Data Interpretation

Integration of AI with multi-omics research has driven major advances in precision medicine by enabling efficient analysis of high-dimensional datasets, facilitating biomarker discovery, improving interpretation of genetic and epigenetic variants, and supporting gene-targeted therapeutic development [51,52]. Deep learning models, in particular, have enhanced variant prioritization and disease-associated mutation detection, improving early diagnosis and personalized treatment strategies.

Beyond biomarker identification, AI-driven network and systems-level analyses provide mechanistic insights into disease pathways relevant to respiratory inflammation, immune dysregulation, and tissue remodeling [53]. These approaches support refined patient stratification, risk prediction, and preventive intervention design. Nevertheless, challenges related to data standardization, model transparency, and clinical implementation persist and require coordinated efforts across research, clinical practice, and regulatory frameworks. Emerging technologies—including federated learning, digital twins, and advanced AI architectures—are expected to further strengthen AI-enabled multi-omics integration and accelerate innovation in respiratory precision medicine.

4. Precision Disease Classification and Prediction

In our observation AI models are increasingly used to classify diseases and predict clinical outcomes using high-dimensional molecular datasets. ML algorithms, including clustering techniques such as XGBoost (eXtreme Gradient Boosting) vector support machines, and random forests, have been applied to DNA methylation, RNA sequencing, and protein data to differentiate tumour subtypes, identify disease-specific molecular signatures, and improve patient classification. The integration of multidimensional datasets further enhances the predictive accuracy of these models, enabling precise disease classification and facilitating the development of tailored treatment strategies. These AI-based methodologies not only improve diagnostic accuracy but also provide actionable insights into the underlying mechanisms of diseases and therapeutic responses. This shift from social and environmental determinants to highly accurate technical evidence underscores the need for a robust, multidisciplinary framework for integrated disease prevention, as summarized in the Table 1.

Table 1. Multi-level analysis of integrated disease prevention: linking social and environmental determinants with epidemiological outcomes.

Socio-Ecological Scale of Intervention	Intervention Modality	Target Diseases	Strategic Objective	Epidemiological Evidence & Outcomes
Molecular Biological-Molecular Determinants	Precision Screening & Biomarker Tracking	Subclinical Metabolic & Inflammatory Disorders	To identify biological mechanisms of disease susceptibility at the cellular level.	Longitudinal studies linking DNA methylation and inflammatory markers to chronic disease onset.
Intrapersonal & Behavioural Factors	Lifestyle Modification Programs	Type2 Diabetes; Cardiovascular Disease	To empower personal health agency and mitigate modifiable behavioural risk factors.	Significant reduction in disease incidence and improved metabolic markers (HbA1c, lipid profiles).
Meso-Social & Community Systems	Community Engagement & Social Support	Infectious Diseases (e.g., COVID-19, TB)	To optimize local resource accessibility and foster collective trust in health interventions.	Improved prevention and control outcomes through culturally competent outreach and local feedback loops.
Macro-Environmental & Structural Governance	Environmental & Macro-Regulatory Actions	Respiratory Disease; Chronic Lung Conditions	To institutionalize health equity through systemic mandates and legislative governance.	Reduced morbidity and mortality rates following the implementation of clean air mandates and tobacco control laws.

Some studies provide a comprehensive review of how AI has achieved remarkable success across diverse biomedical domains, including medical imaging, pathology, and personalized medicine. Key technologies, such as ML, deep learning, and natural language processing, have contributed to improved diagnostic accuracy, predictive modelling, and operational efficiency. AI applications, such as cancer detection, drug discovery, wearable health monitoring, and disease diagnosis, have demonstrated significant clinical and practical impact, with the potential to revolutionize healthcare by improving outcomes and efficiency. However, significant ethical, technical, and societal challenges remain, including algorithmic bias, regulatory gaps, and data security concerns. Addressing these issues requires innovative strategies such as multidisciplinary collaboration, the use of artificial data to train models, and the establishment of robust legal and regulatory frameworks. Continued advances in AI, coupled with responsible implementation, have the potential to transform healthcare systems and pave the way for fairer, more effective, and more accurate medical practices.

Researchers say AI has revolutionized clinical prediction by enabling the analysis of complex datasets, thereby improving early disease detection, prognosis prediction, risk stratification, and personalized healthcare. In diagnostic applications, AI improves detection accuracy, facilitating timely clinical interventions, while in prognosis prediction, it forecasts disease progression and patient outcomes to support treatment decisions. Furthermore, AI supports the management of chronic diseases, identifies individuals at higher risk of hospital readmission, predicts complications, and provides valuable insights into mortality risks. Optimizing the integration of AI into healthcare requires the collection of diverse, high-quality data, interdisciplinary collaboration, and the development of transparent and ethically sound AI systems. Other priorities include physician education and training, rigorous clinical validation, regulatory oversight, and active patient engagement. Continuous monitoring and iterative improvement of AI tools are essential to ensure their safe, effective, and equitable application in clinical practice [54].

5. Integration of Multi-Omics and Clinical Data

AI-based models are increasingly employed for disease classification and clinical outcome prediction using high-dimensional molecular and clinical datasets. ML algorithms, including extreme gradient boosting (XGBoost), support vector machines, and random forest classifiers, have been widely applied to DNA methylation profiles, RNA sequencing data, proteomics, and clinical variables to differentiate disease subtypes, identify condition-specific molecular signatures, and improve patient stratification. The integration of multidimensional datasets substantially enhances predictive performance, enabling more precise disease classification and supporting the development of personalized prevention and treatment strategies.

In the context of chronic respiratory diseases—such as COPD, asthma, pulmonary fibrosis, and environmentally driven lung disorders—AI-driven classification models facilitate early detection of subclinical disease states, risk stratification of exposed populations, and prediction of disease progression. These methodologies move beyond traditional single-risk factor models by incorporating molecular, behavioural, environmental, and epidemiological data into unified predictive frameworks. Importantly, AI-based approaches not only improve diagnostic accuracy but also generate actionable insights into disease mechanisms, therapeutic responsiveness, and population-level risk dynamics. This transition from isolated social or environmental determinants toward integrated, data-driven evidence underscores the necessity of multidisciplinary frameworks for comprehensive disease prevention. Recent reviews highlight the transformative impact of AI across biomedical domains, including medical imaging, digital pathology, and precision medicine. ML, deep learning, and natural language processing have significantly enhanced diagnostic accuracy, predictive modelling, and healthcare efficiency. Applications such as cancer detection, drug discovery, wearable health monitoring, and respiratory disease surveillance demonstrate strong clinical potential. However, ethical, technical, and societal challenges—including algorithmic bias, regulatory gaps, and data security—remain substantial. Addressing these challenges requires multidisciplinary collaboration, robust validation frameworks, and ethically grounded regulatory oversight to ensure responsible AI deployment in public health and clinical practice.

AI has also revolutionized clinical prediction by enabling the analysis of complex and heterogeneous datasets to improve early disease detection, prognosis estimation, and personalized healthcare delivery. In respiratory medicine, AI-based predictive models support early identification of high-risk individuals, forecast disease exacerbations, and guide targeted preventive interventions. Successful integration of AI into healthcare systems depends on high-quality data collection, interdisciplinary collaboration, transparent model design, and continuous clinical validation. Physician training, regulatory governance, and patient engagement are essential to ensure safe, equitable, and effective implementation.

6. AI-Driven Epidemiological Insights for Integrative Disease Prevention

6.1 Lifestyle and Behavioural Interventions

Lifestyle medicine emphasizes the modification of unhealthy behaviours and the promotion of protective habits as core strategies for the prevention and management of chronic diseases. Key behavioural risk factors—including physical inactivity, unhealthy diet, tobacco use, excessive alcohol consumption, and chronic psychosocial stress—are strongly associated with cardiovascular disease, metabolic disorders, cancer, and chronic respiratory diseases. Evidence indicates that sustained adoption of healthy lifestyle behaviours can substantially reduce disease incidence, delay disease progression, and improve long-term health outcomes [54]. Effective implementation of lifestyle interventions requires coordinated, multidisciplinary engagement across healthcare systems and communities. Clinicians play a central role in identifying behavioural risk factors, delivering personalized counselling, and motivating patients to adopt preventive behaviours. Community environments, in turn, provide the social and structural support necessary to sustain long-term behavioural change [55]. Interprofessional collaboration enhances intervention effectiveness, with physicians, nurses, pharmacists, dietitians, behavioural therapists, and social workers each contributing complementary expertise to address medical, psychological, and socioeconomic barriers to behaviour modification [56].

From an epidemiological perspective, integrative prevention strategies that combine behavioural, biomedical, and environmental interventions have demonstrated superior effectiveness compared with isolated approaches [57]. The application of AI now enables large-scale analysis of population-level behavioural and lifestyle data, facilitating early identification of high-risk individuals, prediction of disease trajectories, and optimization of personalized prevention strategies. These capabilities are particularly relevant for chronic respiratory diseases, where behavioural risk factors such as smoking, occupational exposure, and physical inactivity interact with environmental and genetic susceptibility.

6.2 Environmental and Social Determinants of Health

Social cognitive theory describes health behaviour as the product of dynamic interactions among individuals, their behaviours, and their social and physical environments. While awareness of health risks is necessary, sustained behaviour change depends on perceived self-efficacy, outcome expectations, and the presence or absence of environmental barriers. Individuals are more likely to adopt and maintain healthy behaviours when they perceive a sense of control and receive consistent social and structural support [58,59].

Empirical evidence demonstrates that adherence to medical treatment and preventive behaviours is influenced by both personal beliefs and environmental context. Studies applying social learning theory across chronic disease settings—including cancer care and respiratory disease management—show that long-term behaviour change is more sustainable when reinforced through supportive social networks, accessible healthcare services, and enabling policies [60,61]. Environmental change is increasingly recognized as a major driver of emerging and re-emerging infectious diseases and chronic respiratory conditions. Processes such as urbanization, land-use change, biodiversity loss, air pollution, and climate change alter pathogen ecology, exposure patterns, and population vulnerability. These environmental disruptions contribute directly to respiratory disease burden and indirectly to broader public health risks [62,63]. The Environmental Change and Infectious Disease (EnvID) framework provides a systems-based approach for analysing the complex interactions among environmental, biological, and social processes that shape disease transmission and health outcomes. By integrating heterogeneous data sources within a unified analytical structure, the EnvID framework supports hypothesis generation, dynamic modelling, and evidence-based prevention strategies in the context of rapid environmental change [1,53,64].

Integrative reviews further underscore the multidisciplinary nature of environmental health research, emphasizing the need to bridge biomedical, ecological, and social sciences. Contemporary synthesis efforts increasingly link scientific evidence with policy development and community engagement, reinforcing the importance of systems-level approaches for disease prevention and respiratory public health protection [65].

6.3 AI in Interconnected Epidemics and Population Health

The integration of AI into epidemiological systems substantially enhances public health capacity for disease surveillance, outbreak prediction, and population-level risk management. AI technologies—including ML, natural language processing, computer vision, and reinforcement learning—enable early detection of disease outbreaks, real-time analysis of complex datasets, and accurate modelling of transmission dynamics. These tools support proactive decision-making, optimized resource allocation, and adaptive intervention strategies [66]. In respiratory and infectious disease surveillance, AI-driven models analyse heterogeneous data streams such as electronic health records, environmental sensors, mobility data, satellite imagery, and digital media. Natural language processing extracts actionable signals from unstructured sources, including social media and public health reports, enabling early warning and situational awareness. Spatial intelligence derived from remote sensing and geographic information systems facilitates identification of environmental risk hotspots and vulnerable populations [67,68].

Despite rapid technological advances, significant theoretical and practical gaps remain. From a socio-technical systems perspective, many AI applications prioritize predictive accuracy while under-addressing governance, system integration, and human–AI interaction. Limited empirical work examines how AI systems interact with institutional workflows, regulatory frameworks, and ethical oversight in real-world epidemiological intelligence systems. Addressing these gaps is essential for ensuring transparency, accountability, and equitable implementation [69] (Figure 2). Overall, While AI enables large-scale analysis of behavioural data and improves risk prediction, its effectiveness is constrained by biases in self-reported data and unequal digital access, which may limit generalizability and exacerbate health disparities.

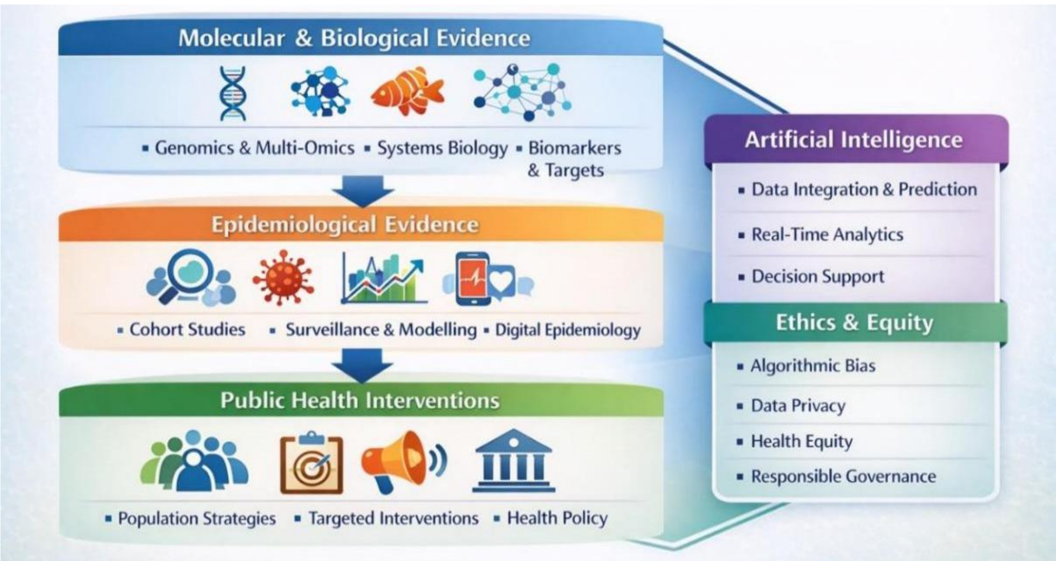

Figure 2. Epidemiological evidence supporting integrative disease prevention: A multi-level intervention frame work.

7. Public Health Frameworks and Their Implications for Policy

AI facilitates integrated approaches to public health by linking epidemiological, social, and environmental data to address complex health challenges. By identifying disease hotspots, uncovering underlying social determinants, and modelling population-level interventions, AI enables targeted prevention strategies and optimal resource allocation. Technologies such as ML, natural language processing, and spatial analysis enhance early detection, predictive modelling, and evidence-based decision-making [16]. These integrated, AI-driven approaches strengthen the capacity of public health systems to manage interconnected epidemics, reduce health inequalities, and improve public health outcomes.

7.1 Digital and AI-Based Approaches in Modern Public Health

Information epidemiology and surveillance, powered by AIand data-mining techniques, enable the analysis of search behaviours, social media communication patterns, and information dissemination trends. These AI-enabled approaches provide real-time insights into disease dynamics, public sentiment, and misinformation. Public health authorities can leverage such insights for early outbreak detection, informed response planning, and the design of effective risk-communication strategies [59,70].

The application of AIin public health information strategies has been geared towards proactive defense against digital infodemics. Rio et al. confirm that, between 2017 and 2025, digital interventions prioritized the identification of false health narratives and the improvement of communication channels to promote public health awareness and combat systemic misinformation [71].

7.2 ML and Predictive Modelling for Outbreak Detection

AI and digital technologies are rapidly transforming disease surveillance and outbreak monitoring, enabling earlier detection, immediate follow-up, and more accurate predictions compared to traditional public health systems. This progress has been extensively documented in systematic reviews and pilot studies, demonstrating that AI-based approaches enhance the ability of surveillance systems to detect unusual patterns indicative of disease outbreaks. By leveraging big data analytics, these systems improve response speed, reduce reporting delays, and provide a more comprehensive understanding of the situation for public health decision-making [72]. ML models can integrate diverse data sources, such as electronic health records, symptom monitoring data, laboratory reports, and spatiotemporal information, to identify disease clusters earlier than traditional surveillance methods. These models support predictive analytics by forecasting disease incidence trends and transmission dynamics, contributing to preparedness planning, resource allocation, and the direction of public health responses [12,73]. The most widely used ML techniques include anomaly detection algorithms, time-series prediction models, and regression-based methods, which analyse temporal and spatial patterns to predict when and where outbreaks are likely to occur.

In advanced modelling frameworks, such as long-term memory neural networks (LSTMs) and isolation forest algorithms, have demonstrated high performance in experimental and applied settings, with detection accuracy exceeding 90% and significant reductions in outbreak reporting delays. Predictive models that integrate diverse data streams—such as clinical indicators, environmental variables, pharmacy sales, mobility data, and wearable device outcomes—improve outbreak probability estimation and hotspot identification, enabling more precise and proactive public health interventions [49,74].

In parallel, new AI-based digital surveillance systems utilize informal and open-source data streams, such as social media and online news. Platforms like Epitweeter, which monitors Twitter activity, and BlueDot, which analyzes global travel patterns and media reports, have demonstrated their ability to provide early warnings about disease outbreaks before official notification mechanisms do. Beyond monitoring outbreaks, AI-powered surveillance models have been applied to track information dynamics and identify spikes in health misinformation linked to behavioural outcomes, such as vaccine hesitancy and changes in vaccination rates. This real-time insight supports the development of effective risk communication and public engagement strategies [75].

Some studies emphasize that expanding AI-based digital interventions to the community level is critical to increasing their effectiveness in public health monitoring and intervention. Large-scale initiatives integrating evidence-based messaging with digital posts have generated millions of user interactions. For example, initiatives like "Dear Pandemic" have garnered over four million views per month, contributing to improved public understanding and health literacy during public health emergencies [76]. More broadly, AI tools are increasingly supporting professional decision-making, improving the response of public health professionals, and strengthening risk communication frameworks. Multidisciplinary expert panels are currently advocating for the integration of AI into comprehensive public health systems, including misinformation management and community engagement strategies on risk.

Despite these advantages, significant limitations remain. Data quality and integrity, algorithmic bias, ethical and privacy concerns, and the need for specialized experts to interpret AI results pose challenges to its widespread adoption. Furthermore, digital data sources, particularly social media, can reflect biases in internet access and user behaviour, requiring careful verification compared to traditional clinical and laboratory surveillance data. Addressing these challenges is crucial to ensuring that AI-based surveillance is integrated into public health systems [77].

7.3 Equity and Ethical Considerations in AI-Based Public Health Systems

Equity is fundamental to comprehensive disease prevention. Underprivileged populations are often more exposed to risk factors and have less access to prevention resources. Therefore, integrated approaches that explicitly address social inequalities are crucial for achieving equitable and sustainable health outcomes. Ethical considerations include ensuring community participation, cultural relevance, and the responsible use of genetic and molecular data in prevention strategies.

The rapid integration of AI into public health infrastructure has led to significant advances in the accuracy of surveillance, the prediction of disease outbreaks, and the effectiveness of risk communication strategies. While these systems promise to improve efficiency and accuracy, evidence suggests that AI can reproduce or exacerbate existing health inequalities if equity considerations are not addressed throughout its lifecycle. Studies indicate that most AI tools in public health are developed and validated using data from urban or high-income settings [78], limiting their applicability to low-resource or marginalized populations. This imbalance threatens to distort the sensitivity of surveillance, misclassify disease risks, and inappropriately allocate public health resources to already underserved communities.

The integrity of AI is fundamentally affected by algorithmic bias. This concern arises when training constructs use data that reflect entrenched social inequalities, leading to outcomes that may reinforce health inequalities rather than reduce them. Empirical studies show that AI models trained on incomplete or unrepresentative datasets consistently underperform when dealing with minority populations. In public health surveillance, this bias can delay the detection of disease outbreaks in rural or poorly connected areas, underestimate the burden of disease in slums, and misclassify risks [79-81]. Bias can emerge through multiple pathways, such as exclusion bias (underrepresentation of certain population groups), measurement bias (differences in data quality between groups), and index bias (using variables related to accessibility rather than actual need). These mechanisms highlight that bias in AI is not merely technical but also deeply social and structural.

Concerns about equity are compounded by unequal access to digital infrastructure and data systems. AI-based public health systems rely heavily on digital data sources, such as electronic health records, mobile phone data, and online platforms, which are unevenly distributed across the population [82,83]. Evidence from low- and middle-income countries suggests that populations with limited internet access, fragmented health information systems, or poor reporting infrastructure are systematically underrepresented in AI-based surveillance outcomes. Consequently, AI systems may prioritize populations already within digital systems, reinforcing existing inequalities in disease detection, prevention, and response.

Data privacy and security are fundamental ethical considerations in the use of AI in public health. Berhane et al. have shown that the reliance of these systems on the collection of large datasets, including people's movements and personal medical history, necessitates strict data protection protocols to reduce the risks associated with mass surveillance and data exploitation. Studies indicate that inadequate data governance frameworks increase the risks of data misuse, re-identification, and unauthorized surveillance, especially in emergencies where ethical safeguards may be compromised [84]. These risks disproportionately affect vulnerable populations, who often have limited capacity to provide informed consent or object to the misuse of their data. Therefore, ethical AI in public health requires robust safeguards for data minimization, secure storage, user anonymization, and transparent consent mechanisms.

As demonstrated by Giles et al. transparency and explain-ability are two fundamental pillars of ethical responsibility in health informatics. Despite their importance, these pillars remain underdeveloped in current AI-based public health architectures, often resulting in opaque systems that obscure the logic underlying clinical and epidemiological decision-making. Complex ML models, particularly deep learning, often act as “black boxes,” limiting the ability of public health practitioners and policymakers to understand or analyze decision-making processes (Table 2). Evidence suggests that the inability to explain undermines trust in AI-based interventions, makes it harder to correct errors, and weakens accountability when harm occurs. This is particularly problematic in public health contexts, where AI-driven decisions, such as prioritizing interventions or issuing public warnings, have far-reaching social consequences [85].

Table 2. A global comparison of ethical frameworks and implementation strategies guiding the use of AI in healthcare.

Risk Category	Critical Challenge	Impact on Healthcare
Data Bias	Dependence on training datasets derived largely from high-income countries or specific demographic groups.	Inaccurate diagnosis and treatment of minorities/ marginalized groups
Black-Box Algorithms	The complex logic of AI that cannot be explained or reviewed by a human doctor.	Loss of clinical confidence and inability to identify the source of medical errors.
Automation Bias	Over-reliance on AI, where human service providers stop questioning the machine's performance.	The possibility of catastrophic errors occurring if the device malfunctions or experiences hallucinations.
Digital Divide	Advanced AI tools are only available to wealthy countries or private clinics.	The growing gap in global health inequalities between low- and middle-income countries and high-income countries.
Data Exploitation	Large-scale collection of health data without proper consent or consideration for cybersecurity.	Violation of patient privacy and misuse of data for commercial purposes

To address these challenges, research is increasingly emphasizing equity-centered, ethically grounded AI governance frameworks. Recommended strategies include using representative and contextualized datasets, conducting regular audits to detect bias and ensure equity, a participatory design process that involves affected communities, and multidisciplinary oversight that combines technical, ethical, and public health expertise. Scoping reviews also highlight the importance of ongoing post-deployment monitoring to detect emerging inequalities and unintended harms over time. Without these safeguards, AI risks becoming a technocratic solution that prioritizes efficiency over equity, rather than a tool that promotes fair and ethical public health practices [86].

8. Future Directions and Research Needs

Despite growing evidence, significant gaps remain in integrated disease prevention research. There is an urgent need to integrate multigenomic data with longitudinal epidemiological studies to elucidate causal pathways and identify high-risk populations, while advances in data science and AIenable the modelling of complex biological and social interactions. Although AI has shown great potential for improving public health surveillance and disease outbreak detection, its application remains uneven, with most evidence coming from high-income settings [1,64].

This underscores the need for context-specific models tailored to regional disease patterns, health system capacities, and social contexts, particularly in low- and middle-income countries.

Future studies should prioritize integrating diverse data sources, including clinical, environmental, mobility, and socioeconomic data, to improve early warning and outbreak prediction. Achieving this requires advancements in data interoperability, governance, and quality assurance to support reliable and timely public health decision-making [87].

Improving the transparency and interpretability of AI models is another urgent research need. Interpretable AI approaches are essential for building trust among public health professionals and ensuring that AI-based insights can be effectively implemented in practice. More robust evidence on real-world performance is also needed. Future research should assess the long-term effectiveness, cost-effectiveness, and public health impact of AI systems compared to traditional surveillance methods.

Finally, future guidelines must continue to prioritize equity, ethics, and capacity building to ensure the responsible use of AIin public health. Reducing algorithmic bias, strengthening governance frameworks, engaging communities, and investing in workforce development are essential for building equitable, ethical, and sustainable public health systems. Meanwhile, despite growing evidence, integrated research on disease prevention remains limited. Greater integration of multigenomic data and longitudinal epidemiological approaches is needed to elucidate causal pathways and identify high-risk populations, while advances in AI and data science provide powerful tools for modelling the complex interactions between the biological and social determinants of health [88,89].

9. Challenges and Considerations

Despite rapid progress, significant limitations remain in the application of AI in public health. The evidence shows a geographical bias toward the Americas and Europe, and disparities in datasets and analytical platforms hinder comparisons between interventions [90-92]. Ethical challenges, such as algorithmic bias, privacy concerns, and unequal access to digital technologies, remain major obstacles to sustainable implementation (Table 2). To address these issues, comprehensive AI policies, robust ethical frameworks, and transparent governance are essential. Integrating the social determinants of health into models, promoting community engagement, investing in education, supporting diverse research funding, and fostering multidisciplinary collaboration are key strategies to ensure that AI technologies are equitable, accountable, and beneficial for all populations [28,93].

10. Conclusion

Integrated approaches to disease prevention represent a significant advance in public health and biomedical research. Evidence from molecular studies supports the biological feasibility of reducing disease risk through targeted environmental and behavioural interventions, while epidemiological research demonstrates the effectiveness of multifactorial prevention strategies at the population level. Public health frameworks facilitate the equitable and sustainable implementation of these interventions. By integrating molecular knowledge, epidemiological findings, and public health actions, this approach provides a comprehensive and effective strategy for reducing the burden of disease and improving public health outcomes.

Conflict of Interest

The authors declare no conflict of interest.

Generative AI Statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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