



Artificial Intelligence-Based Framework for Public Health Crisis Management and National Health Resilience: Opportunities and Challenges

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Abstract

Public health emergencies have become increasingly complex due to the simultaneous emergence of infectious diseases, environmental hazards, climate-related events, technological disruptions, and other large-scale threats. These conditions place substantial pressure on health systems and require rapid, coordinated, evidence-based decision-making. Artificial Intelligence (AI) has emerged as a promising technology for strengthening public health preparedness, surveillance, emergency response, resource allocation, and health-system resilience. Recent evidence indicates that AI can support early detection of health threats, predictive analysis, population health assessment, emergency forecasting, and more efficient allocation of limited healthcare resources. However, the integration of AI into public health crisis management also introduces significant challenges related to data quality, privacy, algorithmic bias, health inequalities, transparency, public trust, cybersecurity, and governance. This review examines the opportunities and challenges associated with the application of AI in public health crisis management and proposes a conceptual framework for strengthening national health resilience. The proposed framework integrates real-time health surveillance, multi-source data integration, AI-based risk assessment, predictive analytics, intelligent decision support, emergency resource optimization, risk communication, and continuous post-crisis learning. The framework is aligned with recent international approaches emphasizing collaborative surveillance, community protection, emergency coordination, evidence-based decision-making, and resilient health systems (World Health Organization [WHO], 2025, 2026). Particular attention is given to the role of trustworthy and explainable AI, human oversight, data governance, and equitable access to AI-enabled public health services. The review argues that AI should not be regarded as a stand-alone technological solution but as part of a broader socio-technical public health ecosystem. Effective implementation requires integration with national emergency preparedness structures, public health institutions, healthcare professionals, community organizations, and policymakers. Overall, the proposed framework provides a conceptual basis for developing adaptive, data-driven, and resilient public health systems capable of detecting emerging threats earlier, responding more effectively to emergencies, maintaining essential health services, and accelerating recovery following major crises.

Keywords: Artificial Intelligence; Public Health Crisis; Health Emergency Management; National Health Resilience; Digital Health; Predictive Analytics; Health Surveillance; Decision Support; Emergency Preparedness; AI Governance

1. Introduction

Public health emergencies have become increasingly complex and multidimensional, requiring health systems to respond simultaneously to infectious disease outbreaks, environmental hazards, climate-related events, humanitarian crises, technological disruptions, and other threats to population health. The COVID-19 pandemic demonstrated that the effectiveness of emergency response depends not only on the availability of medical resources but also on the capacity of health systems to detect emerging threats, integrate information from multiple sources, coordinate institutions, communicate risks, and maintain essential health services during periods of severe disruption (Khatri et al., 2023; World Health Organization [WHO], 2024). Recent approaches to health emergency preparedness therefore emphasize a transition from predominantly reactive models toward integrated systems based on preparedness, surveillance, rapid response, resilience, and continuous learning (WHO, 2024, 2026).

Public health surveillance is one of the fundamental components of effective emergency management because the early recognition of unusual health events can substantially improve the opportunity for timely intervention. Traditional surveillance systems generally rely on structured reporting from healthcare facilities, laboratories, and public health authorities. Although these approaches remain essential, they can face limitations associated with reporting delays, incomplete information, fragmented data sources, and the growing volume and complexity of health-related data. The World Health Organization's recent operational guidance on Early Warning, Alert and Response emphasizes the importance of strengthening surveillance systems to support earlier detection, verification, risk assessment, and response during emergencies (WHO, 2023).

The rapid development of Artificial Intelligence (AI) provides new opportunities to address several of these limitations. Machine learning, deep learning, natural language processing, computer vision, and related techniques can process large and heterogeneous datasets and identify patterns that may not be readily detectable through conventional analytical approaches. Recent research has shown that AI can support disease surveillance, outbreak detection, epidemiological forecasting, health-risk assessment, and public health decision-making by integrating data from healthcare records, digital platforms, environmental sensors, and other information sources (Brownstein et al., 2023; Mendes et al., 2025). AI-based surveillance can also improve the speed and scalability of public health intelligence and support more timely responses to emerging threats.

The potential contribution of AI extends beyond disease surveillance. During emergencies and disasters, health authorities must make rapid decisions regarding triage, hospital capacity, personnel deployment, medical supplies, transportation, and other limited resources. Recent systematic evidence indicates that AI-based approaches can contribute to emergency triage and decision support, although their practical implementation requires attention to data quality, usability, privacy, and the needs of vulnerable populations (Tahernejad et al., 2024). These findings suggest that AI can serve not merely as a diagnostic or analytical tool but as a broader component of emergency management systems capable of supporting multiple functions across the crisis-response cycle.

At the same time, the rapid adoption of AI in public health introduces important ethical, technical, and governance challenges.

AI systems depend heavily on the quality, representativeness, and governance of the data used for development and deployment. Biased or incomplete datasets may result in unequal performance across populations and may reinforce existing health disparities. Privacy and confidentiality are also major concerns because large-scale AI applications may require access to sensitive health and population data. A recent systematic review found that the benefits of AI in public health are accompanied by concerns involving algorithmic bias, privacy, health inequity, transparency, public trust, and governance, demonstrating that AI deployment should be understood as a socio-technical transformation rather than merely a technological upgrade (Gao et al., 2026).

Trustworthy AI is therefore essential for public health crisis management. In high-stakes situations, decision-makers need to understand the basis of AI-generated recommendations, recognize the limitations of models, and retain the ability to challenge or override automated outputs when necessary. Explain ability, transparency, human oversight, validation, and continuous monitoring should consequently be integrated into AI-enabled public health systems from the design stage onward. The World Health Organization has emphasized that AI for health should be developed and deployed in ways that are safe, ethical, equitable, and appropriately governed. Its recent guidance on large multimodal and generative AI systems further highlights the need to address risks associated with reliability, accountability, privacy, and human supervision (WHO, 2024, 2025).

Another important consideration is the resilience of the health system itself. A resilient health system should be capable of anticipating disruptions, absorbing shocks, maintaining essential functions, adapting to changing circumstances, and recovering effectively after a crisis. Resilience therefore extends beyond emergency response and includes governance, workforce capacity, infrastructure, information systems, supply chains, financing, community participation, and continuity of essential services. WHO guidance published in 2024 emphasizes that health-system resilience must be deliberately developed through context-sensitive planning, investment, stakeholder engagement, and coordinated action across the different components of the health system (WHO, 2024).

AI can contribute to health-system resilience by supporting predictive analytics, real-time monitoring, resource allocation, risk assessment, demand forecasting, and decision support. For example, AI-enabled systems may help identify abnormal patterns in population health data, estimate emerging healthcare demand, support prioritization of scarce resources, and improve coordination among public health agencies and healthcare providers. The combination of AI-based surveillance with resilient health-system structures may therefore create a more adaptive emergency-management capability in which information is transformed rapidly into actionable intelligence (Mendes et al., 2025; Gao et al., 2026).

An additional opportunity arises from the integration of AI with digital health infrastructure and public health intelligence. Contemporary emergency-management environments generate information from multiple domains, including clinical records, laboratory systems, epidemiological reports, environmental monitoring, mobility data, social media, and other digital sources. Integrating these heterogeneous datasets can provide a more comprehensive understanding of evolving health risks. WHO's

recent work on global public health intelligence similarly emphasizes a continuous cycle of detection, verification, risk assessment, reporting, and dissemination for acute public health threats (WHO, 2024). AI can potentially strengthen this cycle by accelerating information processing and identifying relationships among complex datasets.

Despite these advances, an important research gap remains. Much of the existing literature focuses on individual AI applications, such as outbreak prediction, surveillance, diagnosis, or emergency triage, rather than examining how these capabilities can be integrated into a unified framework for national public health crisis management and health resilience. Recent reviews have highlighted the need for interoperable systems, stronger validation frameworks, equitable implementation, multidisciplinary collaboration, and adaptive governance mechanisms (Mendes et al., 2025; Gao et al., 2026). This gap provides a basis for developing a comprehensive framework that connects early warning, data integration, risk assessment, predictive analytics, intelligent decision support, resource management, emergency communication, and post-crisis learning within a single resilience-oriented architecture.

Accordingly, this study aims to examine the opportunities and challenges associated with the application of AI to public health crisis management and national health resilience. The paper reviews the major functions in which AI can support preparedness, surveillance, response, recovery, and continuity of essential health services. In addition, it proposes a conceptual AI-based framework that integrates multi-source surveillance, intelligent risk assessment, predictive analysis, decision support, emergency resource management, human oversight, and continuous learning. The proposed framework is intended to provide a practical conceptual basis for future research into adaptive, trustworthy, and resilient national public health systems.

2. Conceptual Foundations of AI in Public Health Crisis Management and National Health Resilience

2.1. Artificial Intelligence in Public Health

Artificial Intelligence (AI) refers to a broad class of computational methods capable of learning from data, recognizing patterns, generating predictions, processing complex information, and supporting decision-making. In public health, the value of AI is particularly associated with its ability to process large and heterogeneous datasets that may include clinical information, epidemiological records, environmental observations, demographic characteristics, mobility patterns, and digital information. Recent research indicates that AI is increasingly being applied to public health surveillance, risk prediction, disease forecasting, health assessment, and emergency response (Ding et al., 2023; Panteli et al., 2024).

Unlike conventional analytical approaches that may require predefined assumptions and structured datasets, AI-based methods can identify complex relationships within high-dimensional data. This capability is particularly relevant to public health emergencies, where information may be incomplete, rapidly changing, geographically distributed, and generated from multiple sectors simultaneously. Consequently, AI can provide an additional analytical layer to conventional public health intelligence rather than replacing established epidemiological and institutional processes (WHO, 2023; Mendes et al., 2025).

2.2. Public Health Crisis Management

Public health crisis management encompasses the coordinated processes used to prevent, prepare for, detect, assess, respond to, and recover from events that create significant risks to population health. Contemporary international frameworks increasingly emphasize that emergency preparedness and response should operate across interconnected systems rather than through isolated institutional mechanisms.

The World Health Organization identifies collaborative surveillance, community protection, safe and scalable clinical care, access to medical countermeasures, and emergency coordination as interconnected components of a resilient health emergency architecture (WHO, 2023, 2024). This perspective implies that effective crisis management requires continuous information exchange and coordination among public health authorities, healthcare organizations, laboratories, emergency services, communities, and other relevant institutions.

Within this framework, AI can function as an analytical and decision-support capability that strengthens several stages of the crisis-management cycle. AI can facilitate early signal detection, risk assessment, forecasting, resource prioritization, and information synthesis, while final decisions remain subject to institutional authority and professional judgment (Panteli et al., 2024; The Lancet Public Health, 2025).

2.3. National Health Resilience

National health resilience refers to the capacity of a health system and the broader institutions supporting population health to anticipate, withstand, adapt to, and recover from disruptive events while maintaining essential functions. Resilience therefore extends beyond emergency response and includes preparedness, governance, workforce capacity, infrastructure, supply chains, information systems, community engagement, and continuity of essential services.

Recent WHO guidance emphasizes that health-system resilience should be developed through integrated planning, coordinated governance, investment in system capacity, and the ability to adapt to changing risks (WHO, 2024). From this perspective, resilience is not a static characteristic but a dynamic capability that evolves through preparedness, response, recovery, evaluation, and learning.

AI can potentially contribute to this resilience by improving situational awareness and enabling health organizations to detect emerging risks earlier, anticipate changes in healthcare demand, identify vulnerable populations, support resource allocation, and continuously update risk assessments. However, AI itself must be incorporated into resilient institutional structures; otherwise, dependence on poorly governed or fragile AI systems could introduce additional systemic vulnerabilities (Gao et al., 2026).

2.4. AI-Enabled Public Health Surveillance

Surveillance is one of the most important areas in which AI can contribute to public health crisis management. Traditional surveillance systems often depend on structured reporting and predefined indicators. Although these systems remain essential, recent developments have expanded surveillance toward collaborative and multisource approaches that integrate information from multiple sectors and levels of the health system (WHO, 2023).

AI can support this transformation by analyzing large amounts of structured and unstructured information, identifying unusual patterns, and prioritizing signals that require further investigation.

Recent reviews describe applications of AI in outbreak detection, epidemiological forecasting, spatial risk assessment, and the integration of emerging digital data sources. Nevertheless, real-world implementation remains challenging because model performance can vary across settings, data quality may be inconsistent, and external validation is still insufficient in many applications (Mendes et al., 2025; Cozzolino et al., 2025).

Consequently, AI-enabled surveillance should be considered a component of a broader collaborative surveillance ecosystem. Human experts, laboratory confirmation, epidemiological investigation, and institutional verification remain essential for converting AI-generated signals into reliable public health intelligence.

2.5. AI-Based Predictive Analytics and Risk Assessment

Predictive analytics provides another important foundation for AI-supported crisis management. Rather than focusing exclusively on current conditions, predictive systems seek to identify potential future developments and support proactive intervention. In public health, this capability may be applied to disease trends, emergency service demand, hospital utilization, population vulnerability, and other indicators of system stress.

The integration of predictive analytics with multisource surveillance can allow public health authorities to move from purely reactive decision-making toward anticipatory management. However, predictions are inherently uncertain, particularly when models are applied to rapidly changing environments. Accordingly, AI-generated forecasts should be interpreted together with uncertainty, data limitations, and expert assessment rather than treated as deterministic predictions (The Lancet Public Health, 2025; Gao et al., 2026).

2.6. Intelligent Decision Support

Decision support represents the point at which analytical information is translated into actionable options for crisis managers. AI can synthesize information from multiple sources, identify significant patterns, compare potential scenarios, and provide decision-relevant summaries. This capability may be particularly valuable when decision-makers face large volumes of information under severe time constraints.

Recent discussions of AI in public health emphasize that its greatest value may arise not from fully automating public health decisions but from augmenting the capabilities of professionals and institutions. Human oversight is therefore essential, particularly for high-impact decisions involving population protection, health resource allocation, and emergency interventions (Panteli et al., 2024; The Lancet Public Health, 2025).

2.7. Data Integration and Interoperability

A national AI-based crisis-management framework requires the integration of information generated by multiple organizations and technological platforms. Fragmented data systems can limit situational awareness and reduce the usefulness of AI models. WHO's collaborative surveillance framework emphasizes multisource and multisectoral information integration as a fundamental component of stronger emergency preparedness and response (WHO, 2023).

Interoperability therefore represents a foundational requirement for the proposed framework. Data from hospitals, laboratories, public health agencies, emergency services, environmental monitoring systems, and other relevant sources should be capable of being combined in a secure and standardized environment. AI can then

operate on a broader information base and generate more comprehensive assessments.

2.8. Trustworthy and Human-Centered AI

The effectiveness of AI in public health depends not only on technical accuracy but also on trust, transparency, fairness, privacy, and accountability. AI systems that produce accurate predictions but cannot be adequately interpreted or governed may encounter substantial barriers to practical adoption.

Recent literature has identified algorithmic bias, unequal access, privacy risks, limited transparency, cybersecurity threats, and insufficient governance as major challenges to the use of AI in public health (Gao et al., 2026). Therefore, trustworthy AI should be considered a core design principle of national health resilience. Human oversight, continuous validation, explain ability, secure data governance, and mechanisms for identifying model failure should be integrated throughout the AI lifecycle.

2.9. Integrated Conceptual Perspective

The conceptual foundations discussed above indicate that AI can contribute to public health crisis management through a connected sequence of capabilities:

Collaborative Surveillance → Data Integration → Early Detection → Risk Assessment → Prediction → Decision Support → Resource Coordination → Response → Recovery → Continuous Learning

Within this model, AI functions as an enabling intelligence layer rather than an independent crisis-management system. Its effectiveness depends on the surrounding institutional capacity, quality of data, interoperability of information systems, professional expertise, governance structures, and community participation. Such an integrated perspective provides the theoretical foundation for developing the AI-based framework proposed in the next sections of this study.

3. AI-Based Early Warning, Risk Prediction, and Outbreak Detection

Early warning and rapid threat detection represent fundamental components of effective public health crisis management. The ability to identify an emerging infectious disease, environmental hazard, or other health threat before it develops into a large-scale crisis can substantially improve preparedness and reduce preventable morbidity, mortality, and economic disruption. Conventional surveillance systems typically rely on clinical reporting, laboratory confirmation, syndromic surveillance, and periodic aggregation of epidemiological information. Although these mechanisms remain essential, their effectiveness may be constrained by reporting delays, fragmented information systems, incomplete data, and limited capacity to process rapidly increasing volumes of heterogeneous information. Artificial intelligence (AI) provides an opportunity to complement conventional surveillance through automated pattern recognition, anomaly detection, predictive analytics, and real-time integration of multiple data sources (Lu et al., 2024).

AI-based early warning systems can continuously analyze epidemiological and nontraditional data to identify signals that may indicate an emerging health threat. Machine learning algorithms are particularly useful for detecting complex relationships that may not be readily identifiable through conventional statistical approaches. Depending on the application, models can analyze hospital admissions, emergency department visits, laboratory results, pharmacy transactions, mortality statistics, environmental

measurements, mobility patterns, and digital communication. The combination of these heterogeneous sources may provide a more comprehensive representation of population-level health dynamics and allow authorities to identify abnormal patterns at an earlier stage.

3.1. Multisource Data Integration for Early Warning

A major advantage of AI-enabled surveillance is its ability to integrate structured and unstructured information. Structured health data can include electronic health records, laboratory results, vaccination records, hospital admissions, and mortality data, while unstructured sources may include clinical narratives, online reports, social media posts, and news content. Environmental and geospatial information can provide additional signals, including temperature, precipitation, air quality, land-use changes, and population mobility.

The integration of these data sources can improve situational awareness by allowing AI systems to identify relationships between health outcomes and contextual factors. For example, changes in environmental conditions may affect the geographic distribution of vector-borne diseases, while mobility patterns can influence the spread of respiratory infections. AI models can therefore move beyond simple case counting toward multidimensional risk assessment in which epidemiological, environmental, demographic, and behavioral variables are analyzed simultaneously.

However, multisource integration also creates substantial technical challenges. Data generated by different organizations frequently use incompatible formats, coding systems, definitions, and temporal or spatial resolutions. Missing observations and inconsistent reporting practices can further reduce model reliability. Consequently, AI-based early warning systems require interoperable data infrastructures and rigorous preprocessing procedures before predictive algorithms can be safely deployed.

3.2. Machine Learning for Outbreak Detection

Machine learning can support outbreak detection by identifying deviations from expected epidemiological patterns. Supervised learning methods can be trained using historical outbreak data, while unsupervised and semi-supervised approaches can identify anomalies when labeled outbreak datasets are limited. Time-series models can additionally analyze temporal changes in disease incidence and estimate whether observed increases represent random variation or potentially meaningful deviations from baseline patterns.

Deep learning approaches have expanded the analytical capacity of outbreak surveillance because they can model nonlinear relationships and high-dimensional datasets. Recurrent neural networks, temporal convolutional architectures, transformers, and hybrid deep learning models can be used for temporal forecasting and sequence analysis. These approaches may be particularly useful when disease dynamics depend on multiple interacting variables. Nevertheless, increased model complexity does not necessarily guarantee improved operational performance. Models must be evaluated using real-world data and clinically meaningful outcomes rather than relying solely on conventional prediction metrics.

An important consideration is the distinction between **signal detection and outbreak confirmation**. AI systems may identify an unusual pattern, but an anomaly does not automatically represent a genuine outbreak. False-positive signals can arise from

changes in reporting behavior, seasonal fluctuations, media attention, changes in diagnostic capacity, or modifications to healthcare-seeking behavior. Therefore, AI should function as an early warning layer that triggers human investigation rather than as an autonomous mechanism for declaring an outbreak.

3.3. Predictive Risk Assessment

Beyond detecting existing abnormalities, AI can be used to predict the probability and potential magnitude of future public health threats. Risk prediction models can estimate the likelihood of disease emergence, geographic expansion, hospitalization, healthcare-system overload, or mortality. By combining epidemiological data with demographic, environmental, mobility, and healthcare-capacity indicators, AI can generate geographically and temporally specific risk estimates.

Such predictive capabilities can support proactive preparedness. If a model identifies a region as having a high probability of increased disease transmission, authorities may increase diagnostic capacity, prepare hospital resources, strengthen surveillance, or intensify risk communication before healthcare demand reaches critical levels. Similarly, predictive models can help identify populations that may be particularly vulnerable during an emergency.

However, predictive risk assessment is subject to uncertainty. Public health systems are dynamic, and interventions themselves can change the variables on which AI models depend. For example, the introduction of vaccination, travel restrictions, behavioral changes, or improved diagnostic capacity may substantially alter disease trajectories. Models therefore need continuous updating and recalibration rather than one-time development and permanent deployment.

3.4. Environmental and Climate-Related Health Threats

The role of AI-based early warning is not limited to infectious disease outbreaks. Climate change and environmental degradation are increasingly associated with complex health risks, including heat-related illness, air pollution, vector-borne diseases, water contamination, and extreme-weather-related emergencies. AI can combine meteorological, environmental, demographic, and health data to identify populations and geographic areas at increased risk. For example, machine learning models can analyze temperature trends and demographic vulnerability to support heat-health warning systems. Similar approaches can be applied to predict periods of increased risk for vector-borne diseases by incorporating temperature, humidity, precipitation, land-use, and vector-distribution data. Such systems can help transform environmental monitoring into actionable public health intelligence.

This application is particularly relevant to national health resilience because climate-related threats frequently cross administrative boundaries and can interact with existing vulnerabilities. A national AI-enabled warning architecture could therefore integrate environmental surveillance with health-system monitoring to provide a more comprehensive assessment of emerging risks.

3.5. Geospatial AI and Population-Level Risk Mapping

Geospatial artificial intelligence represents another important component of advanced early warning systems. Geographic information systems combined with machine learning can generate dynamic risk maps showing where health threats are most likely to emerge or intensify. These maps can integrate population density, healthcare accessibility, socioeconomic characteristics, environmental conditions, transportation networks, and disease indicators.

Spatial risk prediction can support targeted resource allocation. Rather than distributing emergency resources uniformly, authorities can prioritize locations where predicted risk and vulnerability are highest. This may improve the efficiency of vaccination campaigns, testing services, mobile medical units, emergency supplies, and public health interventions.

Nevertheless, geospatial models can reproduce social inequalities when socioeconomic and healthcare-access data are incomplete or biased. Risk maps should therefore be interpreted carefully and validated against local knowledge. Geographic prediction should support equitable resource allocation rather than become a mechanism for neglecting populations that are poorly represented in digital datasets.

3.6. AI and One Health Early Warning

A particularly promising direction is the integration of AI into a **One Health** early warning architecture. Many emerging infectious diseases originate through complex interactions among humans, animals, and ecosystems. Consequently, human health surveillance alone may detect threats only after transmission has already occurred within human populations.

A One Health AI system could integrate human clinical data with veterinary surveillance, wildlife monitoring, environmental measurements, climate information, and ecological indicators. Machine learning could then identify cross-domain patterns associated with pathogen emergence and transmission. Such an integrated approach could support earlier recognition of zoonotic threats and improve coordination among public health, veterinary, environmental, and agricultural authorities.

This approach is especially important for national preparedness because health threats frequently cross institutional boundaries. Effective early warning therefore requires not only advanced algorithms but also organizational mechanisms for sharing information and coordinating action among different sectors.

3.7. Generative AI for Intelligence Synthesis

Generative AI introduces an additional capability: rapid synthesis of large amounts of heterogeneous information. During a public health emergency, decision-makers may receive thousands of reports, scientific publications, situation updates, laboratory notifications, and media reports. Large language models can potentially assist in summarizing these sources, identifying recurring themes, extracting key indicators, and generating preliminary situation reports.

The potential value of this capability is considerable, but so are the associated risks. Generative AI systems may produce plausible but incorrect information, omit critical evidence, or incorrectly interpret ambiguous epidemiological signals. WHO has therefore emphasized the importance of human oversight, transparency, accountability, and rigorous evaluation when large multimodal models are used in health contexts (WHO, 2024; WHO, 2025).

For early warning applications, generative AI should consequently be positioned as an **intelligence-synthesis layer** rather than an autonomous diagnostic or decision-making authority. Its role can be to help analysts process information more efficiently while maintaining human responsibility for verification and interpretation.

3.8. From Early Warning to Early Action

The ultimate objective of an AI-based early warning system is not simply to generate alerts but to enable **early action**. An alert has limited value if the responsible institution cannot interpret it, verify

it, communicate it, and activate an appropriate response. Therefore, AI-based surveillance should be integrated into an operational decision-support framework.

Such a framework can be conceptualized as a sequence of interconnected functions:

Data acquisition → Data integration → AI-based signal detection → Risk prediction → Human validation → Alert generation → Decision support → Resource mobilization → Intervention → Outcome monitoring → Model updating.

This closed-loop architecture can transform AI from a passive analytical technology into an adaptive component of national health resilience. After an intervention is implemented, its effects can be monitored and incorporated into subsequent model updates. Over time, this feedback mechanism can improve both prediction and institutional learning.

The development of such systems requires clear alert thresholds, predefined responsibilities, escalation protocols, cybersecurity mechanisms, and mechanisms for monitoring false-positive and false-negative alerts. Without these operational components, even highly accurate AI models may have limited practical value.

3.9. Limitations and Governance Requirements

Despite significant advances, AI-based early warning systems remain vulnerable to data bias, model drift, incomplete surveillance, adversarial manipulation, privacy risks, and unequal access to digital infrastructure. A model developed in one geographic or epidemiological context may not perform adequately in another. Furthermore, major public health emergencies often involve unprecedented conditions for which historical training data provide limited guidance.

Accordingly, AI-based early warning should be implemented according to a **human-centered, continuously evaluated, and risk-based governance model**. Model performance should be assessed before and after deployment, including across different demographic and geographic groups. Transparency regarding model limitations and uncertainty is essential for preventing inappropriate reliance on automated predictions.

The most effective approach is therefore not to replace traditional epidemiological surveillance with AI but to create a **hybrid intelligence architecture** in which conventional surveillance, expert epidemiological knowledge, AI-based prediction, environmental monitoring, and community-level information reinforce one another. Such integration can improve the speed and breadth of threat detection while preserving human accountability.

4. AI-Enabled Decision Support and Resource Optimization in Public Health Emergencies

Effective management of public health emergencies requires rapid and evidence-informed decisions under conditions characterized by uncertainty, incomplete information, rapidly changing demands, and constrained resources. During large-scale outbreaks, natural disasters, biological incidents, and other health emergencies, decision-makers must simultaneously evaluate disease dynamics, healthcare capacity, population vulnerability, logistics, workforce availability, and intervention effectiveness. Artificial intelligence (AI) can strengthen this process by transforming large and heterogeneous datasets into actionable intelligence and by providing predictive and optimization capabilities for complex emergency-management decisions.

AI-enabled decision support systems can complement traditional epidemiological and administrative approaches by identifying

patterns, forecasting demand, evaluating alternative scenarios, and supporting the prioritization of interventions. Rather than replacing public health experts, these systems can provide an analytical layer that allows decision-makers to examine a larger number of variables and potential scenarios within a limited time. This capability becomes particularly important when the volume and velocity of information exceed the capacity of human teams to process it efficiently (Lu et al., 2024).

4.1. AI-Based Decision Support

Decision support is one of the most important areas in which AI can contribute to public health emergency management. Conventional decision-making frequently relies on predefined protocols and expert assessment. Although these approaches remain essential, they may be insufficient when emergencies evolve rapidly or exhibit characteristics that differ from previous events.

AI-based decision support systems can combine historical data, real-time surveillance information, environmental indicators, healthcare capacity, demographic characteristics, and intervention data to generate risk estimates and potential response options. Machine learning models can identify relationships among variables, while optimization algorithms can evaluate alternative resource-allocation strategies. In this way, AI can help transform complex information into decision-relevant outputs.

A key advantage of AI-supported decision-making is the ability to conduct **scenario analysis**. Decision-makers may need to compare multiple strategies, such as expanding hospital capacity, increasing diagnostic testing, prioritizing vaccination in specific populations, deploying mobile healthcare teams, or reallocating medical supplies. AI systems can estimate the potential consequences of different strategies and provide comparative information to support human judgment.

Nevertheless, the outputs of AI models should be interpreted as probabilistic recommendations rather than deterministic predictions. Public health decisions frequently involve ethical considerations, political responsibilities, and social consequences that cannot be captured completely by computational models. Therefore, human oversight should remain an essential component of emergency decision-support systems.

4.2. Hospital Capacity and Demand Forecasting

Healthcare-system overload represents one of the most serious consequences of major public health emergencies. A rapid increase in patient numbers can exceed available hospital beds, intensive-care capacity, diagnostic facilities, medical equipment, and healthcare personnel. AI-based forecasting can assist health authorities in anticipating these pressures.

Machine learning models can estimate future hospital admissions by incorporating epidemiological trends, demographic characteristics, disease severity, mobility patterns, vaccination coverage, and other relevant variables. Forecasting systems can provide estimates at different temporal scales, ranging from several days to several weeks, allowing hospitals and health authorities to prepare for anticipated changes in demand.

AI can also support the identification of facilities that are likely to experience capacity constraints. Such information can facilitate early redistribution of patients, temporary expansion of capacity, deployment of additional personnel, and transfer of medical equipment. The objective is to move from crisis-driven capacity expansion toward **anticipatory capacity management**.

However, forecasting accuracy can deteriorate when underlying conditions change rapidly. New variants, behavioral changes, changes in clinical practice, or modifications in reporting can alter the relationship between observed indicators and future demand. Consequently, hospital forecasting systems should be continuously updated and evaluated against real-world outcomes.

4.3. Optimization of Medical Resource Allocation

Resource scarcity is a recurring feature of public health emergencies. Vaccines, medications, personal protective equipment, diagnostic kits, intensive-care beds, ambulances, and specialized personnel may be insufficient to meet demand simultaneously across all locations.

AI and mathematical optimization can support the allocation of limited resources according to predicted need, population vulnerability, geographical risk, and healthcare capacity. Instead of relying exclusively on static allocation rules, dynamic systems can continuously update resource priorities as new information becomes available.

For example, an AI-enabled allocation system could identify regions experiencing increasing disease transmission and simultaneously assess their hospital capacity, population density, healthcare accessibility, and vulnerable population characteristics. Resources could then be redirected toward locations where the expected public health benefit is greatest.

Such approaches have the potential to improve efficiency, but resource optimization must incorporate **ethical principles of equity and fairness**. Maximizing the total number of lives saved or minimizing aggregate healthcare demand may not always correspond to equitable distribution. Vulnerable populations, remote communities, and groups with limited access to healthcare may require additional consideration even when their predicted short-term demand is lower.

4.4. Emergency Workforce Management

Healthcare workers represent one of the most critical resources during public health emergencies. Large outbreaks can simultaneously increase demand for healthcare services and reduce workforce availability because of infection, fatigue, psychological stress, quarantine, or competing responsibilities.

AI can assist with workforce forecasting and scheduling by estimating service demand and identifying staffing gaps. Optimization algorithms can be used to distribute personnel across healthcare facilities while considering qualifications, workload, availability, geographical constraints, and emergency requirements.

AI can also support workforce resilience by identifying periods of excessive workload and helping managers design more sustainable shift schedules. This is particularly important because prolonged workforce overload can contribute to reduced performance and increased risk of errors.

However, workforce-related AI applications must avoid treating healthcare professionals as purely interchangeable computational resources. Professional expertise, individual circumstances, and ethical considerations must remain central to workforce decisions.

4.5. Emergency Supply Chains and Logistics

Public health emergencies frequently disrupt conventional supply chains while simultaneously increasing demand for essential medical products. Shortages may result from transportation interruptions, international supply constraints, manufacturing limitations, sudden increases in consumption, or inaccurate

demand estimation.

AI can support emergency logistics through demand forecasting, inventory optimization, route planning, anomaly detection, and supply-chain risk assessment. Predictive models can estimate future consumption of essential materials, while optimization algorithms can identify efficient distribution strategies.

AI-enabled logistics platforms may also integrate information from warehouses, hospitals, transportation systems, and procurement networks. This can provide national authorities with a real-time overview of available supplies and potential shortages.

The importance of such capabilities extends beyond individual emergencies. Maintaining visibility across critical medical supply chains can improve preparedness and allow governments to identify vulnerabilities before a crisis occurs. Consequently, AI-supported logistics can become a permanent component of national health resilience infrastructure.

4.6. Prioritization of Vulnerable Populations

Public health crises rarely affect all population groups equally. Age, socioeconomic status, geographic location, healthcare accessibility, occupational exposure, underlying vulnerability, and other factors can influence both exposure and outcomes.

AI-based risk stratification can assist authorities in identifying populations that may require additional protection during emergencies. Predictive models can combine demographic, clinical, environmental, and socioeconomic indicators to estimate vulnerability at individual, community, or geographic levels.

Such information can support targeted interventions, including vaccination campaigns, preventive communication, mobile healthcare services, testing programs, and emergency assistance.

However, the use of AI for vulnerability assessment presents significant ethical risks. If training datasets reflect existing inequalities, algorithms may unintentionally reproduce or amplify those inequalities. Sensitive characteristics may also be used inappropriately. Therefore, vulnerability models require rigorous fairness assessment, transparency, and governance.

4.7. Digital Twins and Crisis Simulation

An emerging application of AI is the development of **digital twins** for health systems and populations. A digital twin can represent a physical or organizational system computationally and allow decision-makers to explore potential changes before implementing them in the real world.

In public health crisis management, digital twins could potentially represent hospitals, healthcare networks, populations, or entire regions. AI models could simulate different scenarios, such as increased infection rates, hospital surges, vaccination campaigns, supply disruptions, or changes in public-health interventions.

This approach could provide a powerful environment for preparedness planning. Authorities could evaluate hypothetical crisis scenarios without exposing real populations to unnecessary risk. Digital simulations could also identify bottlenecks and dependencies within health systems.

Nevertheless, digital twins require substantial quantities of high-quality data and sophisticated computational infrastructure. Their predictions are also dependent on the assumptions and models incorporated into the simulation. Consequently, digital twins should be considered decision-support environments rather than exact representations of future reality.

4.8. Generative AI and Emergency Intelligence

Generative AI provides a complementary capability for emergency

decision support. Large language models can potentially synthesize epidemiological reports, scientific publications, policy documents, clinical guidelines, and operational updates into concise intelligence products.

During a rapidly evolving crisis, decision-makers may not have sufficient time to examine hundreds of documents individually. Generative AI could assist analysts by extracting key findings, identifying changes between successive situation reports, summarizing emerging evidence, and preparing preliminary briefing materials.

However, generative AI introduces a critical challenge: **plausible misinformation**. A language model can produce fluent and convincing statements that are not supported by evidence. In a public health emergency, such errors could have serious consequences.

Accordingly, generative AI should operate within controlled environments in which outputs can be linked to verified sources and reviewed by qualified personnel. Retrieval-augmented approaches, source verification, confidence assessment, and human approval can reduce—but not completely eliminate—the risks associated with generated information.

4.9. Multi-Criteria Decision-Making

Public health emergency decisions often involve competing objectives. Authorities may need to minimize mortality while maintaining healthcare accessibility, protecting vulnerable groups, preserving essential services, and reducing economic and social disruption.

AI can support **multi-criteria decision-making** by evaluating alternative interventions according to multiple objectives rather than optimizing a single outcome. For example, an emergency response strategy can be evaluated according to expected health impact, cost, resource requirements, equity, implementation feasibility, and time to effect.

This approach is particularly relevant to national health resilience because resilient systems must balance immediate crisis response with long-term sustainability. A strategy that is highly effective in the short term but unsustainable over an extended period may ultimately weaken system resilience.

4.10. Human-AI Collaboration

The successful implementation of AI in emergency decision-making depends on effective human-AI collaboration. AI systems are highly capable of processing information and identifying statistical patterns, whereas human experts contribute contextual understanding, ethical reasoning, institutional knowledge, and responsibility.

The optimal model is therefore a **human-in-the-loop architecture** in which AI generates predictions, alerts, scenarios, and recommendations while authorized experts evaluate and approve actions. Such an architecture can combine computational speed with human judgment.

Decision-makers should also understand the uncertainty and limitations associated with AI outputs. Explainability mechanisms can help users determine why a model produced a particular prediction or recommendation. Transparency is especially important when AI outputs influence resource allocation or interventions affecting vulnerable populations.

4.11. Toward Adaptive Crisis Management

The integration of AI into decision support and resource optimization enables a transition from static emergency plans

toward **adaptive crisis management**. In a conventional model, response plans are prepared in advance and activated when predefined thresholds are reached. An AI-enabled model can continuously monitor conditions, update predictions, evaluate interventions, and modify recommendations as new information becomes available.

The resulting architecture can be conceptualized as:

Situation awareness → Risk estimation → Scenario generation → Resource optimization → Human decision → Intervention → Outcome monitoring → Learning and adaptation.

This feedback loop is fundamental to health-system resilience. Instead of treating each emergency as an isolated event, the system continuously learns from operational outcomes and uses that knowledge to improve future preparedness.

5. Artificial Intelligence and National Health Resilience

National health resilience refers to the capacity of a country's health system and its associated institutions, communities, infrastructure, and workforce to anticipate, withstand, respond to, adapt to, and recover from health-related disruptions. Public health emergencies can simultaneously affect healthcare delivery, medical supply chains, workforce availability, critical infrastructure, economic activity, and public trust. Consequently, strengthening national health resilience requires more than increasing hospital capacity or developing emergency response plans. It requires an integrated capability for continuous risk identification, preparedness, coordinated response, adaptation, and recovery.

Artificial intelligence (AI) can contribute to this objective by providing health systems with advanced capabilities for prediction, situational awareness, resource optimization, decision support, and continuous learning. The strategic value of AI therefore extends beyond individual applications such as disease diagnosis or outbreak prediction. When integrated appropriately into national health infrastructures, AI can function as an enabling technology for developing health systems that are more anticipatory, adaptive, interconnected, and responsive to rapidly changing threats.

5.1. From Crisis Response to Resilience

Traditional emergency management has often emphasized response after a crisis becomes apparent. Although rapid response remains essential, a resilient health system must also be capable of anticipating emerging risks and reducing vulnerabilities before an emergency reaches a critical stage.

AI can support this transition by continuously analyzing epidemiological, environmental, demographic, healthcare, and socioeconomic information. Predictive models can identify changes in risk patterns, while decision-support systems can estimate potential consequences and evaluate preparedness requirements.

The resulting approach can be described as a transition from:

Reactive response → Predictive preparedness → Adaptive response → Continuous learning.

This transformation is particularly important because modern public health threats are increasingly interconnected. Infectious diseases can interact with climate change, population mobility, urbanization, healthcare inequalities, misinformation, and disruptions in critical infrastructure. AI can help analyze these interactions and provide a more comprehensive representation of national health risks.

5.2. Dimensions of National Health Resilience

National health resilience can be conceptualized through several

interconnected dimensions, including **anticipation, absorption, adaptation, recovery, and transformation**.

Anticipation refers to the ability to identify threats before they produce widespread disruption. AI-based surveillance, forecasting, anomaly detection, and environmental monitoring can strengthen this capability.

Absorption represents the capacity of the health system to continue providing essential services while experiencing substantial disruption. AI can support hospital capacity management, workforce allocation, emergency logistics, and prioritization of critical services.

Adaptation involves modifying strategies as the nature of a crisis changes. AI systems can continuously update predictions and evaluate new evidence, supporting dynamic decision-making.

Recovery involves restoring healthcare services and infrastructure after the acute phase of a crisis. AI can support demand forecasting, rehabilitation planning, resource redistribution, and identification of persistent service gaps.

Transformation refers to the ability to learn from crises and redesign systems to reduce future vulnerability. AI can support this process by analyzing historical events, identifying systemic weaknesses, and generating evidence for future preparedness strategies.

These dimensions demonstrate that AI should not be viewed solely as an emergency-response technology. Its greatest contribution may arise when it is integrated throughout the entire resilience cycle.

5.3. AI for National Situational Awareness

National situational awareness is essential for effective crisis management. During a major health emergency, information may be distributed across hospitals, laboratories, public health organizations, emergency services, governmental agencies, environmental monitoring systems, and international sources.

AI can assist in integrating these information streams into a national health intelligence environment. Natural language processing can extract information from unstructured reports, while machine learning can identify trends and anomalies across structured datasets. Geospatial AI can provide spatial representations of risk, while predictive analytics can estimate future conditions.

A national AI-enabled situational awareness system could therefore provide decision-makers with continuously updated indicators related to:

- disease incidence and transmission;
- hospital and intensive-care capacity;
- medical workforce availability;
- pharmaceutical and medical-equipment inventories;
- environmental and climate-related risks;
- population mobility;
- vulnerable populations;
- healthcare accessibility;
- critical infrastructure dependencies; and
- emerging misinformation or public concerns.

Such integration can reduce information fragmentation and improve coordination among national institutions.

5.4. Strengthening Healthcare-System Capacity

Health-system resilience depends heavily on the ability to maintain

essential services during periods of extreme demand. AI can help health authorities anticipate capacity requirements and identify potential bottlenecks before they become critical.

Predictive models can estimate future demand for hospital beds, emergency services, intensive care, diagnostic testing, medications, and specialized personnel. These forecasts can support proactive capacity expansion or redistribution.

AI can also identify relationships between demand and system-level variables. For example, an increase in community transmission may precede increased hospitalization by a predictable interval. Recognizing these relationships can provide hospitals with additional preparation time.

However, resilience should not be measured solely by the ability to accommodate a surge. A resilient system must also maintain routine healthcare services. Excessive concentration of resources on a single emergency may result in delayed diagnosis, treatment interruptions, or reduced preventive care for other conditions. AI-supported resource planning can therefore help balance emergency requirements with continuity of essential health services.

5.5. Resilient Medical Supply Chains

Medical supply chains are critical components of national health security. Disruptions in pharmaceutical production, transportation, international trade, or distribution can rapidly affect healthcare delivery.

AI can strengthen supply-chain resilience through predictive demand forecasting, inventory monitoring, supplier-risk assessment, transportation optimization, and anomaly detection. By integrating information across multiple stages of the supply chain, AI can help identify vulnerabilities before they produce shortages.

A national health resilience platform could potentially maintain a continuously updated representation of critical medical inventories and identify locations where stock levels are approaching predefined risk thresholds. Predictive algorithms could then estimate future shortages based on disease trends and expected demand.

Such capabilities are particularly valuable during emergencies in which demand can increase abruptly and conventional procurement processes may be too slow to respond.

5.6. Workforce Resilience

Healthcare professionals constitute another critical component of national resilience. During prolonged emergencies, workforce shortages may result from illness, burnout, quarantine, excessive workload, or migration between facilities.

AI can assist with workforce forecasting, scheduling, skill matching, and identification of potential staffing gaps. Predictive models can estimate future workforce requirements based on epidemiological and operational indicators.

AI can also help identify patterns associated with excessive workload and operational stress. However, workforce analytics should be implemented with appropriate privacy and ethical protections. Monitoring systems should not become mechanisms for excessive surveillance or punitive performance assessment.

The objective should be to support healthcare professionals and maintain sustainable working conditions rather than merely maximize short-term productivity.

5.7. Community Resilience and Health Equity

National health resilience cannot be achieved solely through institutional capabilities. Communities must also possess the

capacity to access reliable information, obtain healthcare, and respond effectively to health threats.

AI can support community resilience by identifying geographic and demographic disparities in healthcare access, detecting populations that may be underserved, and assisting in the development of targeted public health communication.

AI-enabled systems can also personalize health communication according to language, literacy level, cultural context, and information needs. This capability may improve the accessibility of emergency guidance.

However, personalization can create risks if algorithms classify populations inaccurately or rely on sensitive information without appropriate safeguards. Equity should therefore be explicitly incorporated into AI system design and evaluation.

5.8. Cybersecurity and Digital Resilience

Increasing dependence on AI and digital health infrastructures introduces a parallel challenge: **digital vulnerability**. Healthcare systems are increasingly dependent on electronic records, connected medical devices, cloud infrastructure, communication networks, and digital supply-chain platforms.

A cyberattack or major technological failure during a public health emergency could significantly amplify the original crisis. AI itself can contribute to cybersecurity by detecting anomalous network behavior, identifying suspicious activity, and supporting automated threat monitoring.

At the same time, AI systems can become targets of adversarial attacks, data poisoning, model manipulation, or unauthorized access. Therefore, national health resilience requires cybersecurity strategies that protect both conventional digital infrastructure and AI-specific components.

Security should be incorporated from the design stage rather than added after deployment. This principle is particularly important when AI systems are connected to critical healthcare and emergency-management infrastructure.

5.9. Interoperability and National Digital Infrastructure

The effectiveness of national AI systems depends heavily on interoperability. If hospitals, laboratories, public health agencies, emergency services, and governmental organizations cannot exchange information effectively, AI models cannot provide comprehensive situational awareness.

Interoperability therefore represents a foundational requirement for AI-enabled health resilience. Common data standards, secure communication protocols, consistent definitions, and appropriate governance mechanisms are required to facilitate information exchange.

A national architecture should ideally allow information to move securely across institutional boundaries while maintaining appropriate privacy protections. Such an architecture would enable AI models to operate on broader and more representative datasets while reducing duplication and fragmentation.

5.10. AI Governance and Institutional Capacity

Technology alone cannot create national health resilience. Institutions require appropriate governance structures, regulations, skilled personnel, procurement mechanisms, evaluation frameworks, and accountability systems.

WHO emphasizes that AI in health should be governed according to principles including protection of autonomy, safety, transparency, accountability, equity, inclusiveness, and sustainability (WHO, 2024). These principles become even more

important when AI is deployed at national scale.

National governments should establish clear responsibilities regarding who is authorized to develop, deploy, validate, monitor, and deactivate AI systems. There should also be mechanisms for reporting failures, investigating harmful outcomes, and updating models when performance deteriorates.

Institutional capacity is particularly important because AI systems can become obsolete as data distributions and crisis conditions change. Continuous monitoring and periodic revalidation should therefore be treated as permanent operational requirements.

5.11. AI for Recovery and Post-Crisis Learning

The recovery phase of a public health emergency provides an opportunity to identify weaknesses and strengthen future preparedness. AI can support post-crisis analysis by examining large volumes of operational, epidemiological, and administrative data.

Machine learning can identify patterns associated with successful or unsuccessful interventions, resource shortages, delayed responses, and healthcare-system bottlenecks. Natural language processing can analyze reports and stakeholder feedback to identify recurring problems.

These insights can be incorporated into future preparedness plans. In this sense, AI can facilitate a **learning health system**, in which lessons from each crisis contribute to continuous improvement.

The objective should not simply be to document what happened but to identify why specific outcomes occurred and which structural changes could reduce the probability or impact of future crises.

5.12. A National AI-Enabled Health Resilience Architecture

Based on the preceding discussion, a national AI-enabled health resilience architecture can be conceptualized as a multilayer system.

Layer 1 – Data and Sensing: Clinical, laboratory, epidemiological, environmental, demographic, mobility, infrastructure, and socioeconomic data.

Layer 2 – Data Integration and Governance: Interoperability, data quality management, privacy protection, cybersecurity, data standards, and access control.

Layer 3 – AI Analytics: Machine learning, deep learning, natural language processing, anomaly detection, predictive modeling, geospatial AI, and generative AI.

Layer 4 – Intelligence and Decision Support: Risk assessment, scenario analysis, forecasting, resource optimization, vulnerability assessment, and emergency intelligence.

Layer 5 – Operational Response: Resource mobilization, hospital coordination, emergency logistics, public communication, workforce deployment, and targeted interventions.

Layer 6 – Monitoring and Learning: Outcome assessment, model validation, performance monitoring, post-crisis evaluation, and continuous system improvement.

This architecture establishes a feedback loop in which information generated during response activities returns to the analytical layer and improves future predictions and preparedness.

5.13. Measuring AI-Enabled Resilience

The implementation of AI should be accompanied by measurable resilience indicators. Technical accuracy alone is insufficient to

determine whether an AI system strengthens national health resilience.

Potential indicators include:

- reduction in outbreak detection time;
- improvement in forecasting accuracy;
- reduction in healthcare resource shortages;
- improvement in emergency resource allocation;
- reduction in supply-chain disruption;
- maintenance of essential healthcare services;
- reduction in response time;
- improvement in equitable access to emergency services;
- reduction in preventable mortality;
- workforce sustainability;
- cybersecurity resilience; and
- institutional learning following emergencies.

Such indicators can provide a basis for evaluating whether investments in AI produce meaningful improvements in real-world preparedness and response.

5.14. Strategic Perspective

From a national strategic perspective, AI should be considered part of a broader **health security and resilience ecosystem** rather than an isolated technological investment. The development of AI capabilities should occur alongside improvements in public health infrastructure, epidemiological surveillance, laboratory capacity, emergency logistics, workforce development, cybersecurity, and governance.

The strategic objective is to establish a system capable of continuously answering five fundamental questions:

What is happening?
Where is the threat emerging?
What is likely to happen next?
What resources and interventions are required?
How can the system learn from the outcome?

AI can provide substantial analytical support for answering these questions, but institutional decision-making and accountability must remain human-centered.

Overall, AI has the potential to become an important enabling technology for national health resilience by connecting early warning, predictive intelligence, resource optimization, emergency response, and post-crisis learning. The transition toward AI-enabled resilience, however, requires long-term investment and governance rather than isolated technological deployments. Countries that integrate AI into interoperable, secure, equitable, and human-centered health infrastructures may be better positioned to anticipate emerging threats, reduce disruption, maintain essential services, and recover more effectively from future public health emergencies.

6. Ethical, Legal, Social, and Governance Challenges of AI in Public Health Crisis Management

Although artificial intelligence (AI) offers considerable opportunities for improving public health preparedness, emergency response, and national health resilience, its large-scale implementation also introduces complex ethical, legal, social, and governance challenges. These challenges are particularly significant during public health emergencies because decisions may affect large populations, involve sensitive personal information, influence the allocation of scarce resources, and have

immediate consequences for individual and collective well-being. A recent systematic review of AI in public health concluded that the technology has a dual effect: while it can increase efficiency in surveillance, emergency response, communication, and decision support, it may simultaneously contribute to algorithmic bias, privacy concerns, health inequities, and loss of public trust (Gao et al., 2026).

The central challenge is therefore not simply how to make AI systems more accurate, but how to ensure that their development and deployment remain consistent with principles of human rights, public interest, equity, accountability, and institutional responsibility. This requires AI to be understood as a **socio-technical system** rather than a purely computational technology. Its impacts are determined not only by algorithms, but also by the quality of data, organizational structures, legal frameworks, professional practices, economic incentives, and social context in which the technology operates.

6.1. Privacy and Protection of Health Data

Privacy is one of the most fundamental challenges associated with AI-enabled public health systems. Advanced AI applications require access to large datasets that may contain highly sensitive information, including medical histories, laboratory results, demographic characteristics, geolocation, behavioral information, and health-service utilization.

During a crisis, governments may seek to expand data collection and information sharing to improve surveillance and response speed. However, emergency conditions should not automatically eliminate principles of proportionality, necessity, security, and responsible data governance. Large-scale aggregation of health information can increase the consequences of unauthorized access, data breaches, secondary use, or inappropriate data sharing.

Privacy risks can also emerge indirectly. Even when direct identifiers are removed, combinations of demographic, geographic, temporal, and clinical variables may permit re-identification. AI models can additionally infer characteristics that were not explicitly included in the original dataset. Consequently, privacy protection must extend beyond conventional de-identification and include data minimization, access control, secure computation, auditing, and appropriate governance of secondary data use.

The World Health Organization emphasizes that AI applications in health should respect human dignity, autonomy, and privacy and recommends appropriate governance and oversight throughout the AI lifecycle.

6.2. Algorithmic Bias and Health Inequity

One of the most important risks is the possibility that AI systems reproduce or amplify existing social and health inequalities. AI models learn patterns from historical data. If those data reflect unequal access to healthcare, differences in diagnosis, underrepresentation of specific populations, or systematic disparities in service utilization, the resulting model may generate unequal predictions or recommendations.

Health equity is particularly important in crisis management because emergency resources may be distributed according to AI-generated risk estimates. A biased model could underestimate vulnerability in populations that are poorly represented in digital datasets and consequently direct fewer resources toward those communities.

A 2025 rapid narrative review identified algorithmic bias, unrepresentative training datasets, limited transparency,

accessibility barriers, privacy concerns, and insufficient technical capacity as major health-equity considerations in public health AI. Addressing bias requires intervention at multiple stages. Dataset diversity should be assessed before model development, performance should be evaluated across relevant population groups, and post-deployment outcomes should be monitored for disparities. Fairness should therefore be treated as a continuing performance requirement rather than as a one-time technical adjustment.

6.3. Transparency and explain ability

AI-based decisions can be difficult to understand, particularly when complex deep learning models are involved. In public health emergencies, a lack of explain ability can create significant problems because officials and healthcare professionals must understand the basis, uncertainty, and limitations of important recommendations.

explain ability is particularly relevant when an AI system influences decisions concerning vaccination priorities, allocation of hospital resources, public restrictions, or identification of high-risk populations. Stakeholders need sufficient information to determine whether an output is plausible, whether relevant contextual information has been considered, and whether the result should be trusted.

Transparency should therefore operate at several levels. Users should understand the purpose of the AI system, the types of data being used, the intended population, the system's limitations, and the conditions under which human intervention is required. Full technical disclosure of every computational detail may not always be practical, but operational transparency is essential.

Recent evidence emphasizes explain ability and transparent governance as important mechanisms for building trustworthy public health AI.

6.4. Accountability and Allocation of Responsibility

A critical governance issue concerns the question of **who is responsible when an AI-assisted decision causes harm**. Responsibility may be distributed among system developers, healthcare professionals, public health authorities, technology vendors, data providers, and institutional leadership.

Traditional legal and professional frameworks are often based on human decision-makers. AI introduces situations in which a recommendation may result from complex interactions between data, algorithms, software updates, and user decisions. This can make responsibility difficult to identify.

A resilient governance structure should therefore define accountability before deployment. Organizations should specify who is responsible for model validation, approval, monitoring, incident response, and final decision-making. Human oversight should be meaningful rather than merely symbolic.

The WHO's 2024 guidance highlights the need for stakeholder involvement and government responsibility in establishing standards for AI used in health, while its 2026 report emphasizes stronger ethical oversight of AI-related health research and identifies gaps in existing review mechanisms.

6.5. Human Oversight and Automation Bias

AI may improve decision-making, but excessive dependence on automated recommendations can create **automation bias**. Users may accept an AI-generated recommendation even when contradictory evidence is available, especially during stressful emergencies in which time is limited.

This risk is particularly important for generative AI and large multimodal models, which can produce fluent and highly persuasive outputs. WHO has specifically identified the possibility that users may overlook errors or delegate difficult decisions inappropriately to such systems.

Human oversight should therefore be embedded into system design. Users should be able to challenge AI recommendations, request additional information, override decisions when appropriate, and report failures. The system should also clearly communicate uncertainty and situations in which its predictions are outside the range of validated use.

6.6. Generative AI, Hallucination, and Information Reliability

The rapid expansion of generative AI introduces a distinct category of risk. Unlike conventional predictive models, generative AI systems can produce natural-language content that appears authoritative even when it is inaccurate, incomplete, or unsupported by evidence.

During a health emergency, such errors can influence public communication, clinical decisions, policy interpretation, and emergency planning. Incorrect summaries or fabricated references may be particularly difficult to detect when users are dealing with rapidly changing information.

Consequently, generative AI should be incorporated into public health workflows with mechanisms for source verification, retrieval of authoritative evidence, structured prompts, human review, and post-deployment monitoring. WHO's guidance recommends careful governance of large multimodal models because of risks involving false or incomplete information, bias, cybersecurity, affordability, accessibility, and automation bias.

6.7. Cybersecurity and Adversarial Threats

AI-enabled public health systems also create new cybersecurity vulnerabilities. Health infrastructures contain valuable personal data and increasingly depend on interconnected digital platforms. A successful cyberattack against a national surveillance or hospital coordination platform during a crisis could disrupt both information availability and healthcare delivery.

AI systems may themselves be targeted through adversarial attacks, data poisoning, model manipulation, prompt injection, unauthorized model access, or exploitation of insecure interfaces. An attacker who compromises a prediction system could potentially alter risk estimates and thereby influence emergency resource allocation or public health decisions.

Cybersecurity should therefore be considered an integral component of AI governance. Risk assessment should cover the complete AI lifecycle, including data collection, model training, software integration, deployment, updating, and retirement.

NIST's AI Risk Management Framework provides a structured approach for identifying and managing AI risks, and NIST released a generative-AI-specific profile in 2024. In April 2026, NIST also released a concept note for developing an AI Risk Management Framework profile specifically addressing trustworthy AI in critical infrastructure.

6.8. Legal and Regulatory Uncertainty

AI technologies are developing rapidly, whereas legal frameworks often evolve more slowly. This can create uncertainty concerning data use, liability, safety, regulatory approval, model updates, intellectual property, and cross-border information sharing.

The European Union's Artificial Intelligence Act represents an important example of a risk-based regulatory approach. The

current consolidated EU text establishes requirements for high-risk AI systems, including risk management, transparency, and governance obligations. The regulation has also been amended in 2026, demonstrating that AI governance is itself an evolving policy field.

For public health systems, regulatory approaches should distinguish between applications according to their potential impact. A system used for administrative summarization should not necessarily be regulated in the same manner as one influencing emergency triage or population-level allocation of scarce medical resources.

A risk-based approach can therefore provide greater proportionality by imposing stronger requirements on AI systems whose failure could result in substantial harm.

6.9. Public Trust and Social Acceptance

The long-term success of AI in public health depends heavily on public trust. Individuals may be reluctant to participate in digital surveillance, share health information, or accept AI-supported recommendations if they believe that data are being misused or that decisions are opaque.

Public trust is especially fragile during emergencies because misinformation, fear, political polarization, and uncertainty may already be widespread. AI systems that generate inaccurate content or make decisions perceived as discriminatory can further undermine institutional credibility.

Public acceptance is not determined solely by technical performance. Transparency, perceived fairness, privacy protection, communication quality, and the perceived importance of the task all influence whether people accept AI-supported interventions. Recent systematic evidence indicates that public acceptance of AI in health is context-dependent and closely related to trust, transparency, and the digital divide.

Meaningful public engagement should therefore form part of the governance process. Communities affected by AI systems should have opportunities to understand their purpose, raise concerns, and contribute to discussions about acceptable uses.

6.10. The Digital Divide and Unequal Access to AI

AI may inadvertently widen health inequalities if advanced digital technologies are concentrated in wealthier regions and institutions. Countries and communities with limited computing infrastructure, digital skills, data availability, and financial resources may not benefit equally from advances in AI.

This issue is particularly relevant to low- and middle-income countries. WHO's 2026 report on ethics oversight of AI-related health research specifically identifies inequities affecting low- and middle-income countries, including capacity limitations, power imbalances, data colonialism, ethics dumping, and unequal benefit sharing.

Consequently, a national and international strategy for AI in public health should include investment in infrastructure, workforce development, open standards, research capacity, and equitable access to AI resources. Otherwise, technological progress may increase rather than reduce global health disparities.

6.11. Data Colonialism and Unequal Knowledge Production

The growing use of global datasets and AI models creates an additional concern regarding the ownership and control of health knowledge. Data generated in low-resource settings may be transferred to organizations in technologically advanced countries, where models are developed and commercialized, while the

populations contributing the data receive limited benefits.

This issue raises questions concerning data sovereignty, benefit sharing, research partnerships, local capacity, and ownership of derived knowledge. AI governance should therefore recognize that responsible innovation requires not only protecting individuals from harm but also ensuring fair participation and distribution of benefits.

The WHO's 2026 guidance explicitly highlights data colonialism, power imbalances, ethics dumping, and benefit-sharing concerns in AI-related health research, reinforcing the need for more equitable global governance mechanisms.

6.12. Environmental Sustainability

Large AI models require substantial computing resources, which may increase energy consumption and environmental impacts. As national health systems increasingly adopt AI, the environmental footprint of large-scale computational infrastructure should be considered alongside expected health benefits.

Environmental sustainability is particularly relevant when AI systems are deployed continuously for large-scale surveillance or repeatedly retrained using extensive datasets. Efficient model architectures, appropriate model sizing, shared infrastructure, and energy-aware computing can reduce unnecessary resource consumption.

This suggests that responsible AI governance should incorporate not only health, privacy, and fairness considerations but also environmental sustainability.

6.13. Need for Adaptive and Multilevel Governance

The rapidly changing nature of AI means that governance frameworks cannot remain static. A regulation designed for today's models may not be sufficient for systems deployed several years later. Governance must therefore be adaptive and capable of responding to new technical capabilities and emerging forms of risk.

A multilayer governance architecture should include:

International level: global standards, cooperation, information sharing, and harmonization of principles.

National level: legislation, regulatory agencies, public-sector standards, procurement requirements, cybersecurity policies, and national AI strategies.

Institutional level: organizational governance boards, ethics review, model validation, auditing, incident reporting, and staff training.

Technical level: data quality controls, security mechanisms, model evaluation, fairness assessment, interpretability, monitoring, and version management.

Community level: public participation, transparency, communication, feedback mechanisms, and mechanisms for contesting harmful decisions.

Recent research supports this multilayer approach, arguing that effective governance requires technical standards, ethical oversight, community engagement, and international collaboration rather than reliance on a single regulatory instrument.

6.14. Operationalizing Ethical AI

Ethical principles have limited value unless they are translated into operational procedures. Consequently, health organizations should incorporate ethical requirements into the complete AI lifecycle.

A practical framework can include:

Before

ethical impact assessment, privacy assessment, bias assessment,

deployment:

cybersecurity evaluation, validation, and definition of intended use.

During deployment:

human oversight, performance monitoring, incident reporting, audit trails, access controls, and continuous assessment of fairness.

After deployment:

periodic revalidation, monitoring for model drift, independent audits, stakeholder feedback, impact assessment, and controlled model retirement or replacement.

This lifecycle perspective is consistent with the growing emphasis on post-deployment oversight and independent assessment in international AI governance. WHO recommends independent auditing and impact assessment for large-scale deployment of large multimodal models, while the EU AI Act incorporates risk-management and post-market monitoring requirements for relevant high-risk systems.

6.15. Toward Trustworthy AI for Public Health Crisis Management

The objective of governance should not be to prevent technological innovation but to establish the conditions under which innovation can be trusted. Trustworthy AI in public health should simultaneously address **safety, effectiveness, fairness, transparency, privacy, security, accountability, sustainability, and human oversight.**

These dimensions are interdependent. A highly accurate model may still be unacceptable if it violates privacy. A transparent system may still be harmful if it is biased. A secure system may still fail if healthcare professionals cannot interpret or operationalize its outputs.

Therefore, trustworthy AI should be evaluated through a multidimensional framework rather than a single accuracy metric. This perspective is increasingly reflected in contemporary public health scholarship and international guidance.

7. Proposed AI-Based Framework for Public Health Crisis Management and National Health Resilience

Building on the opportunities, applications, and governance challenges discussed in the previous sections, this study proposes an integrated **Artificial Intelligence-Based Framework for Public Health Crisis Management and National Health Resilience**. The primary objective of the proposed framework is to connect fragmented AI applications into a coordinated national architecture capable of supporting the complete crisis-management cycle, from risk anticipation and early warning to emergency response, recovery, and post-crisis learning.

The proposed framework is based on the premise that AI should not be implemented as an isolated technological solution. Instead, AI capabilities should be embedded within existing national public health institutions, emergency-management mechanisms, health information systems, surveillance networks, laboratories, healthcare facilities, supply chains, and governance structures. This perspective is consistent with recent WHO frameworks emphasizing coordinated national capabilities, surveillance and intelligence, laboratory systems, risk communication, emergency management, workforce development, and evidence-informed decision-making as interconnected components of health emergency preparedness and response.

The framework is designed around seven interconnected layers:

Data and Sensing → Data Governance and Integration → AI Analytics → Risk and Intelligence Engine → Decision Support

and Optimization → Coordinated Response → Recovery, Learning, and Resilience Enhancement.

A continuous governance and cybersecurity layer surrounds all seven components, while human expertise remains embedded throughout the architecture.

7.1. Layer 1: Data Acquisition and Multidimensional Sensing

The first layer is responsible for acquiring data from multiple sources that collectively describe the health status and vulnerability of the population. Public health crises are multidimensional phenomena; therefore, relying on a single surveillance source may provide an incomplete picture.

The proposed framework integrates at least six categories of data:

Clinical and healthcare data: electronic health records, emergency department visits, hospital admissions, intensive-care occupancy, mortality, laboratory results, diagnostic imaging, and healthcare utilization.

Public health surveillance data: confirmed and suspected cases, vaccination coverage, syndromic surveillance, laboratory surveillance, outbreak notifications, and epidemiological investigations.

Environmental data: temperature, precipitation, air quality, water quality, remote sensing, land-use characteristics, and other environmental indicators.

Population and mobility data: population density, transportation activity, migration patterns, mobility indicators, and demographic structure.

Social and behavioral data: public communication, social media trends, health-related searches, community reports, and indicators of public concern or misinformation.

Infrastructure and resource data: hospital capacity, workforce availability, medication inventories, medical equipment, emergency transportation, and critical infrastructure status.

The objective is not to collect the largest possible amount of information. Rather, the objective is to establish a **relevant, timely, representative, and decision-oriented data environment**. WHO's 2025 work on health-data governance emphasizes that high-quality, representative, interoperable, and ethically governed health data are fundamental to reliable AI applications.

7.2. Layer 2: Data Governance, Quality, and Interoperability

Raw data cannot be directly transformed into reliable public health intelligence. The second layer therefore establishes mechanisms for data governance, standardization, quality assessment, interoperability, privacy protection, and cybersecurity.

This layer performs several essential functions, including:

Data cleaning: identification and correction of inconsistent, duplicated, incomplete, or anomalous observations.

Data harmonization: transformation of information from different institutions into compatible formats and definitions.

Data validation: evaluation of data accuracy, completeness, timeliness, and representativeness.

Identity and access management: control over who can access specific datasets and analytical functions.

Privacy protection: application of appropriate privacy-preserving mechanisms and controls.

Interoperability: secure exchange of information among healthcare providers, laboratories, public health agencies, emergency-management institutions, and other authorized organizations.

This layer is critical because an advanced algorithm trained on

biased or incomplete data can produce systematically unreliable results. The WHO's 2025 health-data governance analysis explicitly connects data governance with interoperability, data quality, evidence-informed decision-making, and the development of safe and reliable AI models.

7.3. Layer 3: AI Analytics and Intelligent Processing

The third layer contains the core computational capabilities of the framework. Rather than relying on one AI technique, the architecture uses a collection of complementary methods according to the specific problem.

These capabilities include:

Machine learning: classification, regression, clustering, risk stratification, and prediction.

Deep learning: analysis of complex nonlinear relationships and high-dimensional datasets.

Time-series analytics: detection of temporal trends, changes, and emerging anomalies.

Natural language processing: extraction and synthesis of information from clinical reports, scientific publications, government documents, and digital communication.

Geospatial AI: spatial risk prediction, geographic clustering, vulnerability mapping, and identification of high-risk areas.

Anomaly detection: identification of unusual patterns that may indicate emerging threats.

Generative AI: synthesis of heterogeneous information, preparation of preliminary intelligence reports, and support for communication and analytical workflows.

Optimization algorithms: allocation of limited resources, scheduling, logistics, and intervention planning.

The architecture should employ **task-specific AI rather than indiscriminate use of large models**. A lightweight anomaly-detection model may be more appropriate for a specific surveillance application than a computationally expensive generative model. Similarly, generative AI should mainly perform information synthesis and communication-support functions when these tasks can be controlled through evidence retrieval and human verification.

WHO's current AI strategy emphasizes safe, equitable, evidence-based adoption and the development of sustainable country-level implementation models rather than technology deployment in isolation.

7.4. Layer 4: Risk and Public Health Intelligence Engine

The analytical outputs of individual AI models must be transformed into meaningful public health intelligence. The fourth layer therefore acts as a **risk and intelligence engine**.

This layer integrates multiple predictions to answer four central questions:

What is happening now?

Where is the threat concentrated?

What is likely to happen next?

How severe could the consequences become?

The intelligence engine can generate risk estimates for different hazards, including infectious disease outbreaks, extreme weather, environmental exposure, healthcare-system overload, supply shortages, and other public health threats.

Risk assessment should incorporate not only the probability of an event but also its potential consequences and the vulnerability of affected populations. A geographic area with moderate transmission probability may nevertheless receive a high overall

risk score if healthcare access is limited and hospital capacity is already constrained.

A generalized national risk index can therefore be represented conceptually as:

National Health Risk = Hazard Probability × Potential Impact × Population Vulnerability ÷ Response Capacity

This expression should be interpreted as a conceptual structure rather than a fixed mathematical equation. The variables and their weights should be determined according to the specific hazard and national context.

7.5. Layer 5: Decision Support and Resource Optimization

The fifth layer converts intelligence into actionable options. This is the point at which the proposed framework moves beyond surveillance and prediction toward operational decision support.

The system can provide decision-makers with:

- alternative response scenarios;
- expected healthcare demand;
- predicted hospital congestion;
- resource requirements;
- priority geographic areas;
- vulnerable population groups;
- supply-chain risks;
- workforce requirements;
- estimated intervention impacts; and
- uncertainty associated with each recommendation.

A major feature of the framework is **scenario-based decision support**. Instead of producing a single recommendation, the AI system can evaluate several possible intervention strategies. Decision-makers can compare these strategies according to health impact, resource requirements, equity, feasibility, implementation time, and potential unintended consequences.

For example, when a localized outbreak is detected, the system could compare increased testing, vaccination prioritization, mobile healthcare deployment, additional hospital capacity, or intensified risk communication. The AI system estimates the likely consequences while authorized human decision-makers retain responsibility for the final action.

This approach is consistent with WHO's 2026 discussion of AI and evidence-informed policy, which emphasizes predictive modelling, scenario simulation, adaptive feedback, and the augmentation—not replacement—of human judgment.

7.6. Layer 6: Coordinated Emergency Response

The sixth layer links AI-generated intelligence to the operational response system. An early warning is valuable only when it leads to appropriate action.

The response layer can coordinate:

Healthcare response: hospital surge preparation, patient redistribution, emergency clinical guidance, and workforce deployment.

Public health response: testing, vaccination, contact investigation, surveillance intensification, and targeted interventions.

Logistics: distribution of medicines, medical equipment, protective materials, laboratory supplies, and other critical resources.

Communication: preparation and dissemination of verified public health messages.

Community protection: targeted support for vulnerable populations and areas with limited healthcare access.

Interagency coordination: information exchange and coordination among public health, emergency services, environmental agencies, laboratories, hospitals, and relevant government institutions.

The 2025 WHO National Health Emergency Alert and Response Framework emphasizes coordinated emergency functions across local, subnational, and national levels. The proposed AI framework complements this organizational model by adding an intelligent data and decision-support layer to the existing emergency architecture.

7.7. Layer 7: Recovery, Learning, and Resilience Enhancement

The seventh layer extends the framework beyond the acute emergency. Once the immediate crisis declines, the system enters a recovery and learning phase.

AI can analyze:

- response effectiveness;
- resource utilization;
- delays in decision-making;
- hospital performance;
- supply-chain failures;
- communication effectiveness;
- health outcomes;
- disparities among population groups; and
- unexpected system behaviors.

The resulting information can be used to identify systemic weaknesses and revise emergency plans.

This creates a **closed-loop resilience mechanism**:

Threat detection → Prediction → Decision → Intervention → Outcome → Evaluation → Learning → Model and policy improvement.

The system therefore becomes progressively adaptive rather than repeatedly responding to crises using static plans.

WHO's 2026 framework for national public health agencies explicitly emphasizes assessment of existing capabilities, identification of gaps, prioritization of investments, and adaptation to different national institutional contexts.

7.8. Cross-Cutting Governance, Ethics, and Cybersecurity Layer

Across all seven layers, the proposed architecture incorporates a permanent governance layer.

This layer includes:

Ethical governance: fairness, non-discrimination, proportionality, human rights, and public interest.

Legal governance: compliance with applicable health, privacy, cybersecurity, and AI regulations.

Model governance: documentation, validation, version control, performance monitoring, and controlled updating.

Human oversight: review of high-impact recommendations and authorization of consequential actions.

Cybersecurity: protection against data breaches, malicious manipulation, adversarial attacks, unauthorized access, and disruption.

Transparency: documentation of data sources, model purposes, limitations, uncertainties, and operational thresholds.

Public participation: involvement of healthcare professionals, patients, communities, and relevant stakeholders in system design

and evaluation.

Recent WHO assessments demonstrate that AI adoption is advancing faster than governance in many health systems. In July 2026, WHO/Europe reported substantial gaps in national AI strategies, legal frameworks, professional training, and ethical guidance, highlighting the need to align deployment with governance, infrastructure, and workforce capacity.

7.9. Human-in-the-Loop Architecture

A fundamental design principle of the proposed framework is the preservation of meaningful human control.

The framework distinguishes between three categories of AI output:

Category I – Informational:

AI summarizes, organizes, or visualizes information. Human review remains desirable but the consequences of error are generally limited.

Category II – Advisory:

AI generates risk estimates, forecasts, or recommendations. A qualified human must review the output before consequential action.

Category III – High-impact decisions:

AI contributes to decisions involving substantial risks to individuals or populations. Human authorization is mandatory, and the decision should be traceable and auditable.

This hierarchy reduces the likelihood of inappropriate automation and recognizes that not all AI applications have the same risk profile.

7.10. National Health Resilience Dashboard

A practical implementation of the proposed framework could include a **National AI Health Resilience Dashboard**. The dashboard would provide authorized decision-makers with a continuously updated overview of national health risk and response capacity.

The dashboard could contain five major panels:

Threat Panel: emerging outbreaks, environmental hazards, and abnormal surveillance signals.

Risk Panel: current and projected risk by region and population.

Capacity Panel: hospitals, workforce, laboratories, supplies, and emergency transportation.

Response Panel: active interventions, deployment status, unmet needs, and operational bottlenecks.

Resilience Panel: system performance, recovery indicators, equity indicators, and lessons learned.

Such a dashboard would transform complex AI outputs into a practical operational environment for national and regional decision-makers.

7.11. Implementation Roadmap

The proposed framework should be implemented incrementally rather than through a single nationwide deployment.

Phase 1 – Readiness Assessment

The first phase assesses existing digital infrastructure, data systems, institutional capabilities, workforce skills, legal frameworks, cybersecurity capacity, and current AI applications.

The goal is to identify the most important capability gaps before technological investment begins.

Phase 2 – Data and Infrastructure Foundation

The second phase focuses on interoperability, data quality, secure data exchange, cloud or distributed computing infrastructure, cybersecurity, and standardized data governance.

This phase is foundational because AI performance cannot compensate for severely fragmented or unreliable data.

Phase 3 – Priority AI Pilots

The third phase introduces AI into selected high-value applications, such as outbreak anomaly detection, hospital-demand forecasting, medical inventory prediction, or environmental health alerts.

Pilot projects should be evaluated under real operational conditions rather than solely through retrospective datasets.

Phase 4 – Validation and Independent Evaluation

Models should undergo technical, clinical, epidemiological, ethical, fairness, cybersecurity, and operational evaluation.

Performance should be assessed across relevant demographic and geographic groups and under different levels of data availability.

Phase 5 – Regional and National Scaling

Validated systems can then be integrated across regions and institutions. Standardized interfaces and governance procedures should be used to maintain consistency while allowing adaptation to local conditions.

Phase 6 – Continuous Monitoring and Adaptation

After deployment, AI systems should be continuously monitored for performance degradation, model drift, changing disease patterns, cybersecurity threats, and unintended social consequences.

This phase is essential because AI models should be treated as **living components of the health system**, not as one-time software products.

7.12. Key Performance Indicators

Evaluation of the proposed framework should incorporate both technical and public health outcomes.

Potential indicators include:

Early-warning performance

- time from initial signal to alert;
- sensitivity of threat detection;
- false-positive rate;
- false-negative rate.

Prediction performance

- forecasting accuracy;
- calibration;
- geographic prediction performance;
- temporal stability.

Operational performance

- reduction in emergency response time;
- improvement in hospital capacity planning;
- reduction in critical resource shortages;
- improvement in supply distribution.

Equity performance

- differences in model performance across population groups;
- geographic disparities in intervention access;
- distribution of emergency resources across vulnerable communities.

Governance performance

- percentage of models independently validated;
- frequency of model audits;
- number of reported AI incidents;
- percentage of high-impact decisions receiving human review.

Resilience outcomes

- continuity of essential health services;
- reduction in preventable crisis-related mortality;
- recovery time following major disruption;
- successful implementation of post-crisis corrective measures.

This multidimensional evaluation is important because a model can achieve high predictive accuracy while failing to improve real-world outcomes.

7.13. Risk-Based Prioritization of AI Applications

Not every public health problem requires the same degree of AI sophistication. The proposed framework therefore recommends prioritizing AI applications according to **expected public health benefit, implementation feasibility, data readiness, and potential harm**.

High-priority applications should meet four conditions:

High potential impact + adequate data + feasible implementation + manageable risk.

For example, hospital demand forecasting may represent a relatively practical early application because historical operational data are often available and the outputs can be reviewed by hospital administrators. In contrast, fully automated population-level decisions involving severe restrictions or allocation of life-saving resources should require substantially stronger validation and governance.

This risk-based approach can help governments avoid both underinvestment and uncontrolled technological expansion.

7.14. Alignment with National Preparedness Capabilities

The proposed framework is designed to complement—not replace—established national health emergency structures. WHO's 2026 framework identifies 12 core capabilities for national public health agencies, encompassing foundational capabilities such as legal authority, evidence generation and financing, and technical capabilities including coordination, emergency management, workforce, surveillance and intelligence, laboratory systems, risk communication, clinical guidance, and countermeasure development and deployment.

The AI framework can act as a cross-cutting digital intelligence infrastructure supporting these capabilities.

For example:

Surveillance and intelligence → AI-based detection and forecasting

Emergency management → AI-supported scenario analysis and coordination

Workforce → demand prediction and workforce optimization

Laboratory systems → anomaly detection and epidemiological pattern recognition

Risk communication → evidence-based communication support

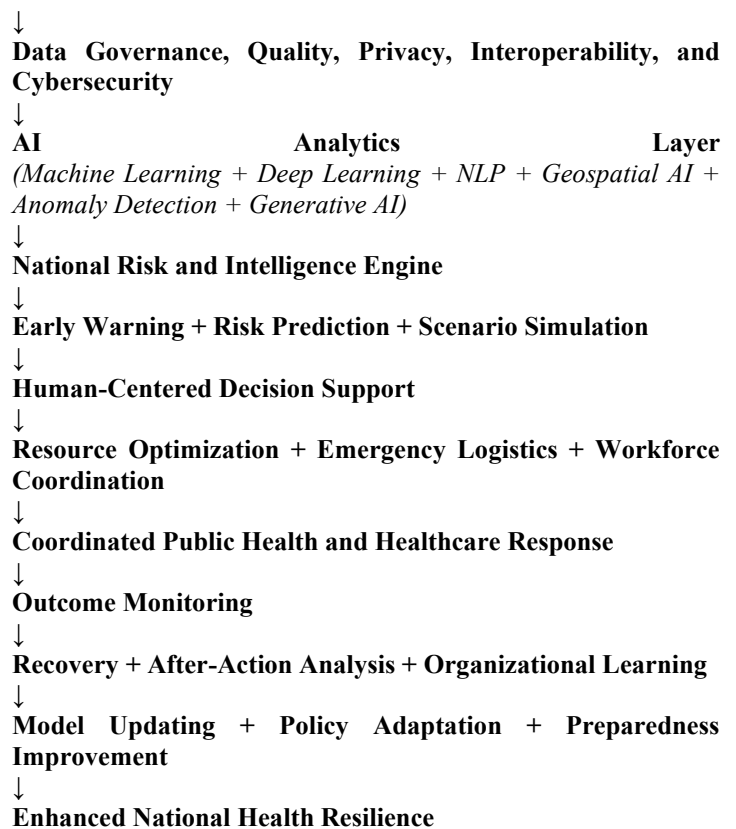
Countermeasures → demand forecasting, prioritization, and logistics

This alignment increases the practical relevance of the proposed framework because AI is integrated into existing public health capabilities rather than creating a parallel institutional structure.

7.15. Conceptual Architecture of the Proposed Framework

The complete conceptual architecture can therefore be represented as:

Multisource Health and Environmental Data



This architecture creates a continuous relationship between information, intelligence, action, and learning. It also ensures that AI is positioned within an institutional system rather than functioning as an isolated predictive technology.

7.16. Expected Contributions of the Framework

The proposed framework contributes to the literature in several ways.

First, it shifts the focus from individual AI applications toward an **integrated national architecture**.

Second, it explicitly connects AI-based early warning with resource optimization, emergency response, recovery, and resilience.

Third, it incorporates governance, ethics, cybersecurity, equity, and human oversight as structural components rather than secondary considerations.

Fourth, it provides an implementation pathway that allows countries to develop AI capabilities progressively according to their digital readiness and institutional resources.

Finally, it creates a feedback mechanism through which lessons from actual emergencies can improve future preparedness and model performance.

The framework is therefore intended to provide both a conceptual and operational foundation for governments, public health agencies, healthcare systems, and researchers seeking to integrate AI into national crisis-management strategies.

7.17. Conclusion of the Framework Section

The proposed AI-based framework represents a transition from fragmented digital applications toward an integrated **intelligent national health resilience ecosystem**. Its central principle is that AI should connect surveillance, prediction, decision support, resource optimization, emergency response, and continuous learning while remaining subject to human oversight and strong

governance.

The framework also recognizes that national resilience cannot be created through technology alone. Effective implementation requires interoperable data systems, capable institutions, skilled personnel, sustainable financing, cybersecurity, ethical governance, public participation, and mechanisms for continuous evaluation.

Recent international developments reinforce this direction. WHO's 2026 national preparedness framework emphasizes coherent institutional capabilities and adaptive implementation, while its 2026 work on AI implementation and evidence-informed policy highlights the need to bridge technological capability with governance, workforce preparedness, validation, and human judgment.

Accordingly, the ultimate value of AI in public health crisis management should be measured not by the sophistication of algorithms deployed, but by whether these technologies enable health systems to **anticipate threats earlier, make better decisions, allocate resources more equitably, maintain essential services, recover faster, and learn continuously from crises**. This principle provides the foundation for the subsequent evaluation of opportunities, implementation barriers, and future research priorities.

8. Opportunities and Challenges of AI in Public Health Crisis Management

Artificial intelligence provides major opportunities for transforming public health crisis management from a predominantly reactive process into a predictive, adaptive, and data-driven system. The most important opportunities include earlier detection of emerging threats, improved outbreak forecasting, real-time situational awareness, optimized allocation of medical resources, hospital demand prediction, emergency logistics, targeted intervention, and improved evidence synthesis. AI can also strengthen national health resilience by connecting surveillance, decision support, emergency response, recovery, and organizational learning.

Despite these opportunities, several challenges may limit effective implementation. These include poor-quality or fragmented data, limited interoperability, algorithmic bias, privacy concerns, cybersecurity threats, lack of transparency, model uncertainty, hallucination in generative AI, insufficient skilled personnel, high infrastructure costs, regulatory uncertainty, and unequal access to digital technologies. Excessive dependence on automated recommendations may also create automation bias and weaken human judgment.

Another major challenge is ensuring **health equity**. AI systems trained on incomplete or unrepresentative datasets may perform less effectively for specific demographic or geographic populations and may unintentionally reinforce existing inequalities. Therefore, fairness, inclusiveness, and continuous evaluation should be integrated throughout the AI lifecycle.

Overall, the future value of AI in public health depends less on algorithmic sophistication alone and more on the development of a **secure, interoperable, ethical, human-centered, and continuously learning national health ecosystem**. Successful implementation requires simultaneous progress in technology, governance, infrastructure, workforce capacity, cybersecurity, and public trust.

9. Future Directions and Research Priorities

Future research should focus on transforming AI from isolated predictive tools into integrated and operational components of national public health systems. Priority should be given to developing interoperable AI architectures capable of combining epidemiological, clinical, environmental, demographic, and social data in real time.

Research is also needed to improve the **generalizability, fairness, explain ability, and robustness** of AI models across different populations and crisis conditions. Continuous model validation, uncertainty estimation, and detection of model drift should become standard components of emergency AI systems.

Another important research direction is the development of **multimodal and generative AI** for public health intelligence, while establishing reliable mechanisms for source verification, hallucination reduction, privacy protection, and human oversight. Future studies should also investigate AI-supported digital twins, One Health surveillance, climate-related health forecasting, emergency logistics, and adaptive resource optimization. Importantly, research should evaluate not only technical performance but also real-world outcomes such as reduced response time, improved health equity, continuity of essential services, and faster recovery.

Finally, greater attention should be devoted to **AI governance and implementation in low- and middle-income countries**, where limitations in infrastructure, data availability, financing, and workforce capacity may restrict adoption. International collaboration, standardized evaluation frameworks, capacity building, and equitable access to AI technologies will be essential for ensuring that future advances contribute to global—not merely high-resource-country—health resilience.

10. Conclusion

Artificial intelligence (AI) has the potential to fundamentally transform public health crisis management and strengthen national health resilience. By integrating real-time surveillance, early warning, risk prediction, decision support, resource optimization, emergency logistics, and post-crisis learning, AI can help health systems move from predominantly reactive responses toward more predictive, adaptive, and resilient approaches.

The proposed framework emphasizes that the value of AI does not depend solely on the performance of individual algorithms. Effective implementation requires integration with reliable data infrastructures, interoperable health information systems, skilled human resources, cybersecurity mechanisms, ethical governance, and existing national emergency-management structures. Human oversight must remain central, particularly for decisions with significant consequences for individuals and populations.

At the same time, major challenges—including privacy risks, algorithmic bias, unequal access, misinformation, cybersecurity threats, limited transparency, model uncertainty, and regulatory gaps—must be addressed before large-scale deployment. Responsible AI therefore requires continuous evaluation throughout the system lifecycle, together with mechanisms for accountability, fairness, transparency, and public participation.

Overall, AI should be viewed not simply as a technological tool, but as a component of a broader **national health resilience ecosystem**. Its greatest contribution will occur when predictive intelligence is effectively converted into timely, equitable, and evidence-informed action. Future research and policy should therefore focus on developing trustworthy, interoperable, adaptive,

and human-centered AI systems capable of supporting countries in anticipating threats, maintaining essential health services, responding effectively to emergencies, recovering rapidly, and learning from each crisis.

The integration of AI with public health preparedness can ultimately provide a pathway toward stronger national health security and more resilient health systems. The success of this transformation, however, should be measured not by the sophistication of AI technologies themselves, but by their demonstrated ability to improve population health outcomes, reduce inequalities, accelerate emergency response, and strengthen the capacity of health systems to withstand future crises.

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