Dissertation Report
at

CARPL.ai

AI in Disease Surveillance and Forecasting: Transforming Population Health

A Report
By

Dr. Simran Kaur Antal
PG/23/117

Under the guidance of

Dr. Altaf Yousuf Mir

PGDM Hospital and Health Management
2023-2025

IIHMR DELHI

International Institute of Health Management Research, New Delhi

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(Completion of Dissertation from respective organization)

The certificate is awarded to

DR SIMRAN KAUR ANTAL

in recognition of having successfully completed her
internship in the department of

CUSTOMER SUCCESS AND ACCOUNT MANAGEMENT

and has successfully completed his/her Project on

AI in Disease Surveillance and Forecasting: Transforming Population Health

(Feb 24 to May 24, 2025)

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She comes across as a committed, sincere & diligent
person who has a strong drive & zeal for learning.

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I wish her success in all her future endeavors.

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Associate Dean, Academic and Student Affairs
IIHMR, New Delhi

Mentor

IIHMR, New Delhi

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Nikki Pandey	
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Name of the Student: Dr. Simran Kaur Antal

Name of the Organisation in Which Dissertation Has Been Completed: CARPL.ai

Area of Dissertation: Customer Success and Account Management

Attendance: 100%

Objectives achieved:

1. Maintained documentation on Confluence for all key accounts in the LATAM region.
2. Created and maintained JIRA tickets for all incoming customer requests, bugs raised and incident requests for sprint planning discussions.
3. Participated in external client calls and ensured timely follow-up through emails.

Deliverables:

1. Coordinated the go-live for a new client site, ensuring all technical, validation, and communication steps were in place for a smooth launch.
2. Regularly compiled and shared comprehensive monthly updates for all LATAM region accounts.
3. Created AI validation projects for the clients and ensured client acceptance and satisfaction.

Strengths:

1. Quick learner
2. Good at taking accountability of assigned tasks and ensuring completion
3. Good interpersonal skills
4. Proactive

Suggestions for Improvement:

1. With growing experience, they have the potential to communicate with more confidence when interacting with clients and external partners.

Suggestions for Institute (course curriculum, industry interaction, placement, alumni):

Dhruv Gautam

Signature of the Officer-in-Charge/ Organization Mentor (Dissertation)

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ABSTRACT

The use of Artificial Intelligence (AI) in public health is transforming the field of disease surveillance and prediction. The use of AI technologies in population health, with particular emphasis on their application in early detection, outbreak prediction, and preparedness of health systems, has been discussed in this thematic review. In a secondary analysis of 25 peer-reviewed studies, the research determines salient themes including the development of AI models, real-time processing of data, predictive analytics, and ethics. From the findings emerges AI's capability to process large volumes of heterogeneous health datasets to produce actionable intelligence, enhance epidemiologic forecasting, and aid data-driven policymaking. With challenges still existing in algorithmic bias, privacy of data, absence of standardization, and infrastructural constraints, these and other challenges need to be further addressed. The research highlights the importance of transparent, ethical AI systems co-designed with public health stakeholders to deliver equitable benefits across populations. These findings are important for building stronger global health surveillance systems and pandemic preparedness.

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OBSERVATIONAL LEARNING

SECTION-1: INTRODUCTION

ABOUT CARPL:

CARPL.ai is the world's first testing and deployment platform for medical imaging AI applications, which connects healthcare providers to third party AI applications, helping improve access, affordability, and quality of medical care.

It bridges the gap between healthcare providers and AI developers by serving as a gatekeeper that seamlessly connects both sides of the ecosystem. In essence, it is a single interface to access AI algorithms, validate and test them, and subsequently embed them into radiology workflows.

It is used by some of the world's leading healthcare providers, AI researchers, industry teams and startups. It is built with the single goal of making it easy for clinicians to get access to advanced analytics tools.

VISION

CARPL's vision is to be the back-end platform behind all medical imaging AI deployment globally by becoming the single interface for AI deployment at healthcare providers, and the go-to-market strategy of choice for AI developers.

FEATURES

Easy to Access: There is a fragmented ecosystem out there if any HCP wanted to deploy any radio diagnostic AI solution how they can contact AI developers providing similar solutions individualistically, but CARPL platform have 100+ AI solutions of different AI developer on a simple single user- friendly platform.

Easy to Assess: CARPL is the first company to provide the feature of Validation and Testing & Monitoring of the AI solutions for the HCPs so they can analyze the efficiency of the AI model over their own Patient data.

Easy to Integrate: If the HCPs starts deploying AI solutions related to radiodiagnosis by multiple AI developers for different use cases they would require different RISPACS integrations but for accessing multiple AI solutions via CARPL requires single RIS-PACS setup.

Reliability: All the AI solutions onboarded on CARPL's platform are regulatory compliant including FDA(US), CE(Europe), HSA(Singapore), ANVISA(Brazil) and TGA (AUS).

PROJECT REPORT

Chapter 1

1.1 INTRODUCTION

The 21st century has seen unprecedent growth in artificial intelligence (AI), revolutionizing virtually every aspect of human endeavor including health. With rising global health risks, from infectious disease outbreaks to new pandemics, the need for reliable, real-time disease surveillance and prediction systems has never been more urgent. AI has new tools that can quickly synthesize data, identify patterns, and forecast, making it a force of transformation in public health.

Conventionally, disease surveillance depended upon paper-based reporting systems and back-end analyses, which tend to fall. behind real-time events. This can prove to be disastrous, particularly for outbreaks such as COVID-19 or Ebola [1].. AI, led by machine learning (ML), natural language processing (NLP), and big data analysis, reinforces epidemiologist's capability to track, predict, and react quickly to public health emergencies.

Population health, by definition, is interested in health outcomes and their distribution in groups of people. It necessarily requires timely data across a broad variety of datasets from electronic health records (EHRs), social media, climate trends, to mobility and demographic datasets. Artificial intelligence is called the simulation of human intelligence processes by robots or computer systems. It is a field of computer science that has the capacity to transform the delivery of healthcare and medical practice AI helps in real-time disease monitoring, precise prediction of outbreaks, and customized disease risk analysis [2].

In this era surrounded by pandemics, zoonotic spillovers, antibiotic resistance and climatic change health emergencies, the need for accurate, timely, and scalable surveillance frameworks is immense. Artificial intelligence is being increasingly integrated into public health infrastructure to deliver early outbreak warnings, forecast disease trends, and maximize healthcare resource allocation [3].

The use of AI for disease surveillance and forecasting is no longer speculative but evidentially established through several global case studies. For example, with the COVID-19 pandemic, AI technologies such as BlueDot and HealthMap effectively warned health authorities about the virus's propagation days prior to official announcements. Whereas the technological potential of AI is well-proven, the actual deployment of AI in public health is accompanied by deep issues regarding data quality, bias of algorithms, transparency, and regulation [4]. Various scholars point out that AI can be a trusted partner in global health only if it is used ethically and inclusively.

This research looks at how AI can be used in population health across several fields, with a focus on disease surveillance and forecasting.. It seeks to unpack major thematic areas, review research, and critically examine the ethical and functional challenges shaping the existing and future state of AI-based public health systems.

1.2 RATIONALE

The COVID-19 pandemic presented many challenges to global health infrastructures but also illustrated the strength of digital and AI driven tools in responding to large scale health emergencies. Several platforms such as BlueDot and HealthMap showed the capacity to identify disease signals before official notification [5]. Nevertheless, AI use in public health practice is uneven, with ethical, infrastructural, and contextual constraints affecting its adoption and impact.

There exists a need to assess the existing situation of AI application in disease surveillance and forecasting by conducting a review of the available literature. Secondary thematic review provides an overarching view by aggregating the scattered evidence base, recognizing key themes, and delineating gaps that should be bridged for AI to realize its potential in population health.

1.3 RESEARCH QUESTION

How is AI being used in population health for disease surveillance and prediction, and what key themes, challenges, and ethical concerns influence its impact?

1.4 OBJECTIVES

The primary objectives are -

- To explore current trends and developments in the use of AI for disease surveillance, prediction, and control.
- To classify the types of AI models (e.g., ML, DL, NLP) used in epidemiological applications.
- To identify common challenges, limitations, and ethical considerations in applying AI in public health.

CHAPTER 2 REVIEW OF LITERATURE

2.1 EVOLUTION OF AI IN PUBLIC HEALTH

The history of artificial intelligence in healthcare traces its roots back to the 1960s, when scientists first started trying to match human intelligence using computing systems. The early advance moved through expert systems, This approach was the leading edge until the 1980s and 1990s, although the decade also saw growing attention given to machine learning and NLP approaches.

The 2000s witnessed a breakthrough with sensational advancements in machine learning, computer vision, and NLP. It became feasible to develop advanced diagnostic systems based on these technologies, e.g., those that could analyze medical images to detect diseases like cancer. Text mining was later used to enable scientists to harvest meaningful information from large and frequently unstructured data sources, e.g., electronic health records.

Of late, AI has gained popularity in public health, particularly predictive analytics and disease surveillance. Algorithms have been used to forecast outbreaks of diseases such as influenza and COVID-19, enabling the authorities to implement timely interventions. AI has been used in analyzing big data on social media and elsewhere to detect nascent health threats [6]. With greater computing power and access to data, applications of AI have expanded to include personalized medicine and drug discovery.

Public health surveillance systems are enhanced from manual data collection to artificial intelligence and big data-driven predictive systems. Initially, surveillance involved manual reporting and basic statistical tools, which limited timely action and early identification of public health hazards. The turning point came in the 1990s with the emergence of electronic health records (EHRs) and automation technologies for data capture [7]. This shift to digital enhanced data precision, accelerated reporting, and established the potential for more sophisticated analysis capabilities. By the early 2000s, information technologies supported greater and deeper integration of data analytics in public health.

It was then that artificial intelligence and machine learning entered healthcare, and surveillance systems could detect complex patterns in health data. The technologies made it possible to create predictive models that were able to determine impending health threats in advance before they escalated into crises. The trend shifted public health planning from response to reactive responses towards proactive planning that was guided by trend forecasting.

The 2010s brought another leap with the use of big data in healthcare. Unstructured and structured data from EHRs to social media inputs, wearable technologies, and environmental sensors became the focus of surveillance [8]. With the capacity to gather and process huge, varied datasets in real-time, healthcare providers could detect trends that were not possible with legacy systems.

2.2 TYPES OF AI MODELS IN HEALTHCARE

Artificial Intelligence systems are normally classified into three: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI).

Artificial Narrow Intelligence (Weak AI) is created to accomplish concrete tasks within a narrow area of expertise. Such systems never extend their abilities outside their trained domains. Examples of this include virtual assistants like Siri and Alexa, which execute voice commands and recommendation algorithms employed by streaming services such as Netflix.

Artificial General Intelligence seeks to simulate human level mental flexibility such as reasoning, learning to perform multiple tasks, and abstract reasoning. Originally conceived as AI that learns and functions like people, AGI has had to be redefined because machines lack the qualities of intuition, moral reasoning, and self-awareness unless specifically programmed.

Artificial Superintelligence is a hypothetical future in which AI exceeds human intellectual and emotional abilities. Although popular to talk about, its possibility is doubtful. For practical applications, most notably in public health or pandemic control, the prevailing types of AI are still based on narrow, predictive algorithms as opposed to genuinely general intelligence.

Machine Learning (ML): Machine learning is a branch of AI and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy [9].

Deep Learning (DL): Deep learning is a method in artificial intelligence (AI) that teaches computers to process data in a way that is inspired by the human brain. Deep learning models can recognize complex patterns in pictures, text, sounds, and other data to produce accurate insights and predictions [10].

Natural Language Processing (NLP): It is the discipline of building machines that can manipulate human language — or data that resembles human language — in the way that it is written, spoken, and organized [11].

Large Language Models (LLM): A large language model (LLM) is a type of artificial intelligence (AI) algorithm that uses deep learning techniques and massively large data sets to understand, summarize, generate and predict new content [12].

To fully understand how AI systems learn is crucial to understand how they are utilized in healthcare and other fields. These systems are learnt using massive data sets and learn by employing various strategies, mostly belonging to machine learning (ML).

1. Supervised Learning

This approach uses labelled data for training, matching each input with the appropriate output. It is frequently used for classification tasks (like filtering spam emails) and regression activities (like predicting home prices).In the medical field, it is often utilized to identify known anomalies in diagnostic images.

2. Unsupervised Learning

Employed when data does not have pre-defined labels, this method attempts to find implicit structures in data. It encompasses:

- Clustering: the collection of similar things, e.g., patient types.
- Dimensionality reduction: simplifying data through reducing variables.
- Anomaly detection: finding uncommon data points, beneficial in recognizing system failures or fraud, such as hidden problems in infrastructure like wastewater systems.

3. Reinforcement Learning

In this case, an AI agent learns from experience through interacting with an environment and being rewarded or penalized. Techniques include:

- Value-based: determining the value of given actions.
- Policy-based: improving the strategy that directs decision-making.
- Model-based: employing a model of the environment to guide planning.

Although perhaps most famously associated with gaming, reinforcement learning is increasingly manifest in healthcare e.g., in systems that integrate clinical evidence and expert opinion in order to support early diagnosis of conditions such as sepsis [13].

In current public health surveillance, machine learning models are a key component of improved disease detection, outbreak prediction, and facilitating proactive intervention. The most significant of these models include Artificial Neural Networks (ANNs), Random Forest algorithms, and Support Vector Machines (SVMs), each playing a unique role in population health monitoring and predictive analysis.

2.2.1 Disease Surveillance with Neural Networks

Artificial Neural Networks have revolutionized the field of public health analytics through allowing the processing of enormous, unstructured epidemiological data. They can detect subtle, non-linear patterns in the spread of disease, which might go undetected using conventional statistical methods. By combining several sources of data everything from electronic health records to social media and environmental data neural networks are able to identify emerging threats to health more and more precisely as they continually re-tune themselves based on new information. Both risk factors and transmission dynamics of disease can be identified with their help. Sophisticated variants like deep learning models have further stretched these capabilities.

2.2.2 Random Forest Models for Population-Level Risk Assessment

Random Forest models, via ensemble learning, are the go-to choice in public health due to their ability to effectively manage variable, multi-dimensional data. Random Forest models use many decision trees to offer high-precision predictions of disease risk and progression. Random Forests are particularly well-suited for environments with missing or heterogeneous data typical scenarios in population health data with clinical, demographic, and environmental data.

2.2.3 Support Vector Machines in Early Detection Systems

Support Vector Machines (SVMs) have proven to be strong tools in the enhancement of the accuracy of early disease detection. SVMs are particularly good at recognizing intricate, high-dimensional patterns of health data through the optimization of hyperplanes separating disease states with distinction [8]. This positions SVMs as especially well-suited for early warning systems for infectious diseases, where accurate classification is critical.

SVMs have enhanced sensitivity and specificity in surveillance systems, allowing for quicker and more accurate detection of emerging health threats. Their ability to handle structured (e.g., lab reports) as well as unstructured data (e.g., clinician comments) increases their application across various surveillance contexts.

2.3 APPLICATIONS OF AI IN PUBLIC HEALTH

Artificial intelligence technologies now enable the analysis of vast, complex data sets faster and better than with traditional methods, enhancing the ability to spot patterns and provide early notification of disease outbreaks and epidemics. One example is the Centre for Disease Control and Prevention (CDC) employing AI in the COVID-19 pandemic [6].

Artificial intelligence systems are particularly effective at detecting unusual patterns and signals that could signal the onset of infectious diseases, enabling timely interventions by health authorities. Social media monitoring algorithms, for example, can detect symptom-cue words, serving as virtual early warning systems against impending public health hazards [3]. This is a major improvement over traditional methods with the bane of delayed reporting of data and slow analysis.

2.3.1 DISEASE SURVEILLANCE

The two fields of public health that gain most from the increased application of AI are surveillance and preventive medicine. AI can detect patterns and forecast epidemics ahead of their spread through data analytics and machine learning algorithms. For instance, computer programs search through vast amounts of data from various sources, including travel history, social media posts, and medical records, to pick up early warning signals of infectious diseases.

By analyzing airline travel patterns, news sources, and animal disease outbreaks, BlueDot identified Wuhan, China, as a possible epicenter of a new infectious disease and issued early warnings to global health officials [14]. Such predictive capacities indicate the ways in which AI can enhance conventional epidemiological approaches towards the advancement of tracking and management of public health threats.

In addition to infectious diseases, AI can also be useful in tracking non-communicable diseases like cancer, diabetes, and cardiovascular disease. By analyzing patient records, AI can identify high-risk populations, making it possible to treat them earlier and hopefully save healthcare costs [4]. For instance, AI platforms that integrate lifestyle markers, clinical histories, and wearable device real-time data can estimate the risk of cardiovascular events, allowing personalized prevention management.

2.3.2 PREDECTIVE ANALYTICS

By enabling the shift from reactive to proactive care, predictive analytics has revolutionised public health surveillance.. Through the use of complex mathematical modeling, AI and ML models, health systems can screen various sources of data for patterns, predict outbreaks, and begin interventions on time.

Research indicates predictive analytics improve significantly early disease diagnosis and resource deployment compared to classical forecasting techniques. Success factors are high-quality information, smooth integration, and organizational preparedness, but issues such as data normalization and interoperability persist. These results identify the potential for transformative change of predictive analytics in improving public health results with timely and appropriate action and indicate that attention needs to be given to technical, organizational, and ethical aspects for effective implementation.

In predictive infectious disease, combining epidemiological information with machine learning has been very accurate, even above 85-92% using models such as artificial neural networks that reveal intricate transmission patterns. Using various data types such as environmental, social, and genetic data further narrows down predictive models to respond to emerging trends. Crowdsourced online data and the use of ML algorithms have made it possible to track diseases in real-time with high accuracy, enabling public health officials to predict outbreaks weeks in advance [8].

In recent pandemics, ML algorithms showed more than 90% accuracy in forecasting transmission patterns, specifically aiding resource-constrained environments by giving early warnings to ready healthcare facilities. Such collaboration between ML and traditional epidemiology drives a more nimble and responsive public health system. Predictive analytics have also been useful in the aftermath of chronic conditions such as diabetes, COPD, and cardiovascular diseases by allowing for early detection, tailored treatment, and active surveillance.

Performance analysis identifies deep neural networks and state-of-the-art algorithms like gradient boosting, random forests, and support vector machines as offering high accuracy, precision, recall, and F1 scores in disease prediction. These technologies process intricate, multivariate data such as structured clinical reports, unstructured text, and real-time sensor inputs to facilitate subtle predictions of disease progression and risk.

Technological advancements in chronic disease care also focus on empowering patients using platforms to support active self-management and individualized care. The future is to blend innovative predictive models with patient centered strategies to provide accurate, anticipatory healthcare interventions that enhance system effectiveness and patient outcomes.

2.3.3 RISK PREDICTION

Risk forecasting is critical in public health for proactive prevention and management of diseases. Conventional approaches involving clinic and demographic information are slow and at times unreliable. AI enhances prediction and speed by processing massive amounts of data such as electronic medical records, genomics, and medical imaging to identify risk for diseases.

Progress in AI, technology in wearable devices, and genomics provide more accurate and timely information to make enhanced predictions. Explainable AI (XAI) improves transparency by revealing models' decision-making processes, building more trust in AI applications in healthcare [6].

AI is better suited to identify people at greater risk by combining varied data sources and detecting intricate patterns that go undetected with conventional methods.

2.3.4 SPATIAL MODELING

Spatial modelling is the study of geographic information which helps to identify health patterns and plays a major role in targeting public health interventions to areas with high risk. AI enhances these models by taking large-scale geographic data such as satellite images and separating trends and predicting the spread of disease.For example, AI techniques have been used to forecast dengue fever cases, peak season, and risk factors like mosquito activity.

The coupling of AI and Geographic Information Systems (GIS) supports handling large volumes of sources like medical records and social media with respect to location to improve prediction accuracy and identify latent patterns. Emerging AI approaches, such as deep learning, can handle intricate data like genomics and imaging data to identify local disease risk, as seen through neurological and respiratory disease studies [6].

GIS combine spatial data, mapping technology, and visualization tools to map and analyze patterns, trends, and associations of disease outbreaks. GIS help public health professionals identify areas of high risk through cluster detection of cases, patterns of transmission, and at-risk populations, distribute resources more effectively, and use targeted interventions to limit the spread of disease [15]. This strategy enables authorities to predict patterns of transmission, measure movement of populations, and contrast the likely effects of varied intervention activities and thus enhance decision-making, planning for resources, and epidemic management.

2.3.5 PRECISION PUBLIC HEALTH

AI is revolutionizing public health by making possible precision public health and customized medicine beyond the one-size-fits-all approach to data-driven, customized interventions. Traditionally, public health interventions impacted populations indiscriminately as a whole [16]. Using AI, interventions and treatment are today personalized according to an individual's genes, environment, and behaviors for improved outcomes.

Artificial intelligence platforms like IBM Watson for Oncology analyze genetic data and available research to guide clinicians in making optimal treatment decisions, like cancer treatment. This reduces guesswork and optimizes patient care through timely, targeted treatments.

On a broader level, AI ensures precise public health by identifying at-risk groups and tailoring interventions in response to specific needs. This targeted effort helps in minimizing health disparities and maximizing equity [4].

2.3.6 AI AND HEALTH INEQUITY

Artificial intelligence technologies can significantly enhance the delivery of healthcare services using improved diagnosis procedures, reduced waiting times, and lower costs. For instance, algorithms can be used to assist in diagnostics, making health more accessible and efficient. Electronic health technologies such as the application of drones have the potential to eliminate geographic barriers, ensuring that important health services reach marginalized communities [17].

However, implementing AI effectively in such settings is a matter of overcoming challenges like poor internet connectivity, absence of digital literacy, and demand for culturally sensitive instruments [4]. Enabling equitable access to AI is about ensuring that these matters are carefully considered in a bid to access all segments.

2.4 ETHICAL AND LEGAL CHALLENGES

There are several ethical, legal, and infrastructure challenges in the application of AI to healthcare and epidemiology research. These transcend technical capability and engage with core problems of trust, equity, responsibility, and readiness. In the following, this section defines five important dimensions that must be addressed to facilitate the proper use of AI in public health settings.

2.4.1 Explainability and Public Trust

One of the principal barriers to the successful integration of artificial intelligence into public health is a lack of transparency as to how AI systems operate. That lack of knowledge generally leads to distrust and overexpectation on the part of medical providers.

The COVID-19 pandemic showcased the vast potential of AI for use such as tracking virus spread and predicting hotspots of outbreaks. At the same time, it made obvious that transparent and trustworthy AI systems, especially in times of crisis, are a necessity. Merging Explainable AI (XAI) techniques with theoretical practices from various disciplines can build trust among health professionals so that AI can be utilized responsibly and patient-centered. Fostering transparency, ethical commitment, and explainability is thus critical to achieving broader acceptability of AI in public health.

2.4.2 Data Equity and Integrity

AI technologies usually require access to large data sets for effective training and verification. Ensuring the confidentiality and integrity of PHI is not only important for maintaining patient confidence but also to be compliant with regulations like the Health Insurance Portability and Accountability Act (HIPAA) [18].

The accuracy, completeness, and impartiality of data on which AI relies are all important in ensuring the efficacy of AI for public health. Nevertheless, some underlying, ingrained issues such as restricted access to data, data systems incompatibility, and representation of the demographics fall behind time and again to make it tough for creating robust AI models.

For example, AI projects such as the DeepMind collaboration with Moorfields Eye Hospital exhibited shortcomings related to inconsistent image quality and variability in clinical conditions. That points toward end-to-end data approaches being particularly valuable. Initiatives like the European Health Data Space aim to harmonize data collection across systems, mixing electronic health records, behavior data, and social determinants to build stronger, bias-reduced models. Prioritizing the integration of diverse, high-quality data will optimize the value of AI and avoid having its outputs disregard diversity in the world around us and concerns about health equity.

2.4.3 Ethical Governance and Dual-Use Risks

There are no standards governing the application of AI in health systems, which is one of the biggest hurdle to mass introduction. Public health AI tools have double purposes clinical and administrative. Without proper guidelines these purposes may lead to ethical concerns such as privacy, autonomy, or misuse of data.

To fill this gap, a common framework has to be developed for regulating the design, testing, and deployment of AI systems in health care. Interoperability between digital health systems, as well as adherence to ethical standards of AI, is necessary for effective and safe use. For instance, social media-based AI mental health screening programs showcase the urgent need for regulative protection against misuse and obtaining consent [19]. The EU AI Act represents one type of policy that results from ongoing efforts to risk-regulate yet still foster innovation.

Getting the right balance between technological advancement and moral responsibility is the most critical element in sustainable AI adoption.

2.4.4 Human Oversight and Clinical Accountability

While AI algorithms can parse vast data sets and decide patterns more effectively, their output is not absolute, especially when deployed in dynamic real-world settings. In the absence of backstops for ongoing human supervision, AI recommendations can be lacking in context or propagating unknown biases.

This ongoing monitoring through human in the loop concept is especially important in high-risk cases like diagnosis or treatment planning. Recent studies such as the mistakes output by large language models in cancer care suggestions present the risks of over-reliance on AI without professional validation [20]. Formalization of roles for clinicians and public health professionals in the AI process raises reliability and supports ethical decision-making. Training professionals to engage with AI critically and assuredly will guarantee the technology enhances, and does not replace, human judgment.

2.5.5 Infrastructure and System Readiness

Deploying AI within public health rests on a strong technological infrastructure with the capacity for high-volume, high-velocity data while also protecting personal information. Most health systems, especially in low-resource environments, have neither secure, scalable infrastructure nor the mechanism to build, test, and keep AI models running. Without proper system readiness, even the most sophisticated AI tools cannot be meaningfully integrated or supported.

The COVID-19 outbreak provided important lessons in this sense, especially through contact tracing and outbreak prediction with the help of AI. These applications highlighted the potential of real-time data analysis but also exposed shortcomings in privacy safeguards and digital infrastructure. In the future, investments in secure cloud infrastructure, encrypted databases, and dependable data pipelines will be important [21]. Moreover, transparent privacy policies need to be incorporated into AI systems in order to preserve public confidence.

CHAPTER 3 METHODOLOGY

3.1 STUDY DESIGN

This study follows a secondary review done to explore the role of Artificial Intelligence (AI) in disease surveillance and prediction for population health.

3.2 LITERATURE SEARCH STRATEGY

Databases Searched

- PubMed
- Scopus
- Google Scholar
- ScienceDirect

Keywords and Boolean Operators

- "Artificial Intelligence" OR "AI"
- "Disease Surveillance"
- "Epidemiology" OR "Public Health"
- "Predictive Modeling" OR "Forecasting"
- "Big Data" AND "Machine Learning"

3.3 PRISMA FLOW DIAGRAM

21 articles were shortlisted following screening and full-text eligibility assessment.

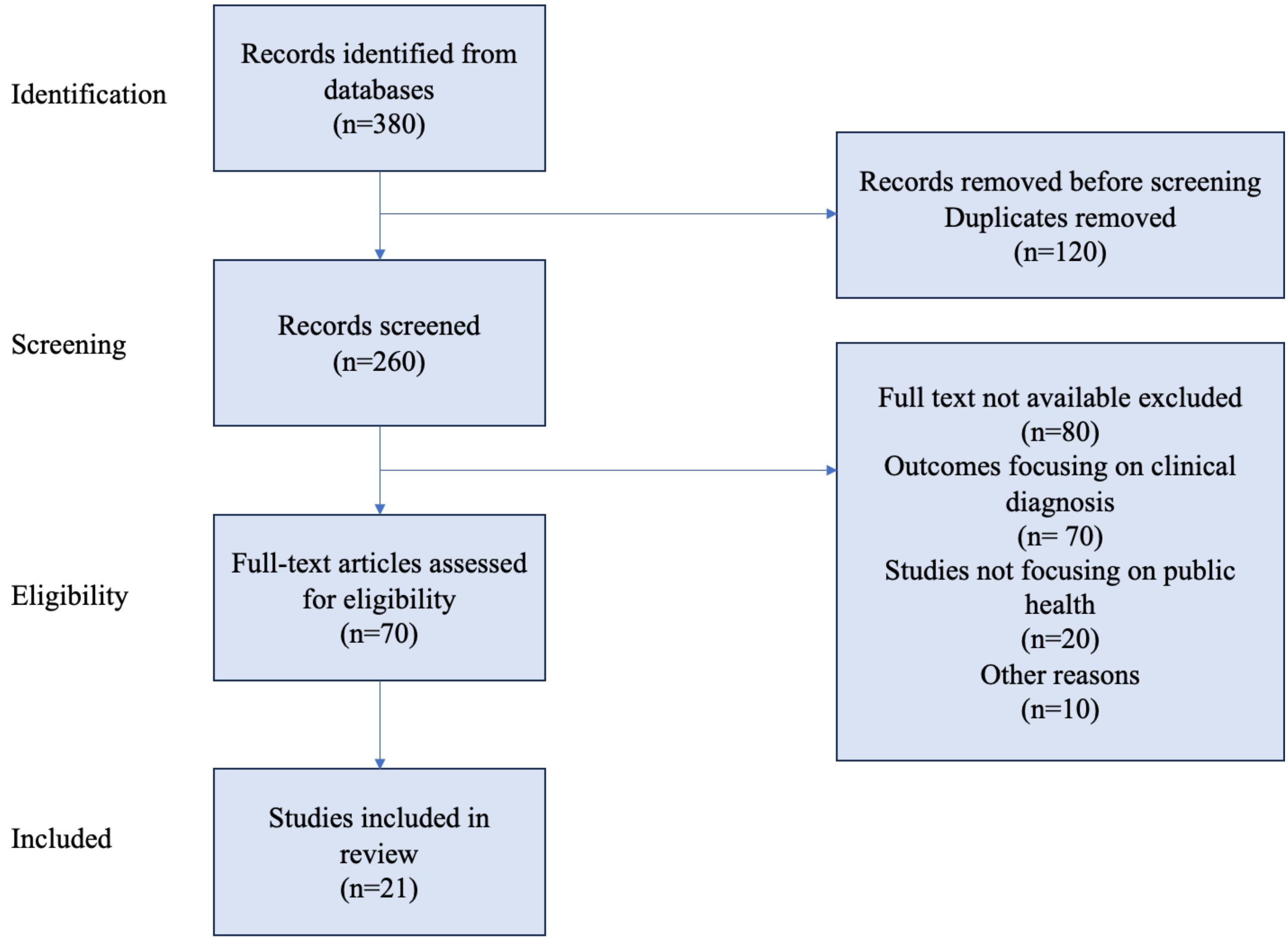


Figure 1: PRISMA Flow Diagram

3.4 INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria

- Peer-reviewed journal articles (2018–2025)
- Articles focusing on AI in disease surveillance or prediction
- Studies in English
- Research focused on public/population health

Exclusion Criteria

- Articles not available in full text
- Conference abstracts, posters, and editorials
- Studies unrelated to public health or AI
- Articles focusing solely on AI for clinical/individual diagnosis

3.5 THEMATIC ANALYSIS APPROACH

Braun and Clarke's six-step thematic analysis model was used to identify themes in the chosen secondary literature. Steps undertaken included:

1. **Familiarization with the Data**

   All included articles were read thoroughly to gain an in-depth understanding of the content. Key observations, significant concepts, and initial reflections were documented to support the development of preliminary ideas.

2. **Generating Initial Codes**

   Meaningful data segments were systematically coded using a codebook that captured recurring features such as use-cases of AI, ethical challenges, outbreak prediction, and system-level factors. These codes provided the foundation for identifying broader patterns across studies.

3. **Searching for Themes**

   The generated codes were grouped into potential themes that reflected underlying trends in the literature, including areas such as predictive analytics, algorithmic bias, applications in disease surveillance, and public health decision-making.

4. **Reviewing Themes**

   The themes were carefully reviewed to ensure internal consistency and distinctiveness. Redundant or overlapping themes were merged or removed, refining the thematic structure and improving clarity.

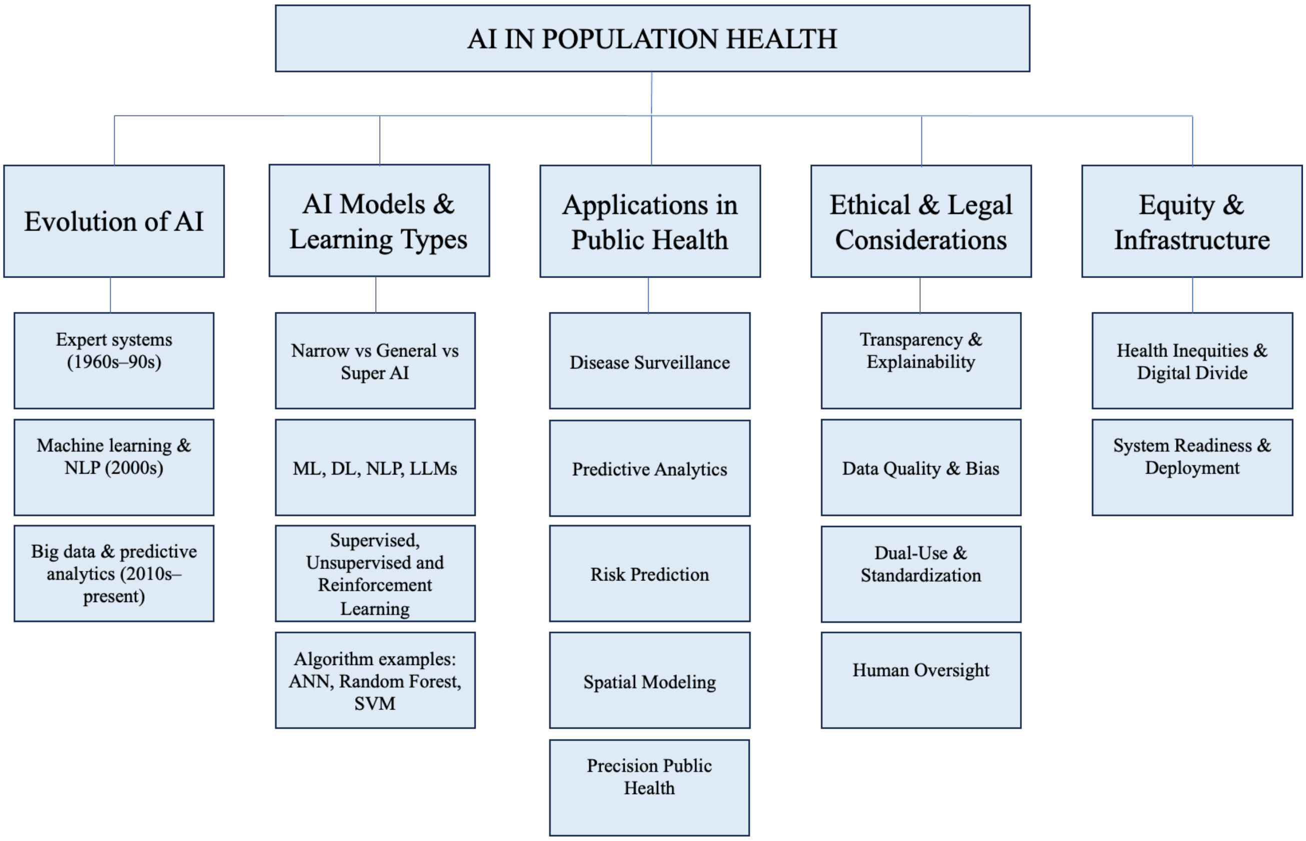
5. **Defining and Naming Themes**

   Each theme was clearly defined to reflect its specific focus and relevance to the study. Finalized theme names included examples such as *evolution of AI*, *AI models, applications of AI, Ethical Constraints in AI Use, and Implications for Policy and Governance*.

6. **Producing the Report**

   The final themes were integrated into a coherent analytical narrative presented in the Results and Discussion chapters. Themes were aligned with the research questions and used to draw conclusions and propose recommendations for the responsible integration of AI into public health systems.

3.6 THEMATIC CODE TREE



CHAPTER 4
RESULTS AND THEMATIC ANALYSIS

4.1 THEMATIC MATRIX

Theme	Sub-Theme	Key Points	Sources
AI Evolution	Historical Milestones	AI moved from expert systems → ML/NLP → real-time surveillance with big data	[6]
	EHRs & Cloud Integration	EHR digitization enabled predictive public health systems	[8]
AI Models & Learning	Types of AI	ANI, AGI, ASI distinctions; current use mainly ANI	[9] [10]
	ML, DL, NLP, LLMs	Technical methods for healthcare analysis, text mining, and predictions	[11] [12]
	Learning Types	Supervised, unsupervised, reinforcement learning used across diagnostics, clustering, planning	[13] [8]
Applications	Disease Surveillance	COVID-19, BlueDot case, AI + social data integration for early detection	[6] [3]
	Predictive Analytics	85–92% accuracy in disease prediction; crowd-sourced + structured data integration	[8]
	Risk Prediction	IBM Watson, explainable AI for chronic and acute conditions	[6]

	Spatial Modeling	GIS + AI for dengue, neurological disease tracking; satellite data + social data used	[15]
	Precision Public Health	Targeted interventions; reducing disparities via AI personalization	[16] [4]
Ethical Issues	Transparency	Black-box risks, XAI needed for clinical trust	[18]
	Data Bias	Skewed datasets, poor quality data = inaccurate predictions; need for diversity	[19]
	Dual-Use & Governance	AI tools used for both care and surveillance → regulation needed	[20]
	Human Oversight	"Human-in-the-loop" is essential; current LLM risks in clinical accuracy	[21]
Health Equity	Access and Digital Divide	AI tools reduce disparities (e.g., diagnostics, telehealth) but need contextual adaptation	[17]
	Infrastructure & Readiness	Low-resource settings lack infrastructure; data pipelines and privacy policies crucial	[4]

4.2 SUMMARY OF FINDINGS BY THEME

Theme 1: Evolution from Manual systems to AI driven prediction

A common thread throughout the literature is the progression of public health surveillance from reactive systems to predictive, AI-driven platforms. Previous systems were much dependent on manual data entry and basic statistical software, constraining their responsiveness to developing threats. The merging of electronic health records (EHRs), automated pipelines for data, and real-time monitoring via wearables and sensors revolutionized the pace and extent of health data collection.

Advances now allow for predictions of disease outbreaks, moving public health policy to one of anticipatory action. BlueDot is an example of how machine learning programs can recognize initial indicators of outbreaks from global data feeds (e.g., travel, news, social media), otherwise unseen in conventional epidemiological platforms. This proactive shift is essential in controlling future pandemics, delivering quicker warnings, improved planning, and lighter healthcare loads.

The theme emphasizes how AI is not so much an efficiency tool it is a conceptual shift of public health to prevention and anticipation, radically changing surveillance paradigms.

Theme 2: Typology and Function of AI Models in Epidemiology

Although conversation regularly brushes against Artificial General Intelligence (AGI) or Artificial Superintelligence (ASI), real-world applications of AI in public health are controlled by Artificial Narrow Intelligence (ANI). The literature points to the prevalence of supervised learning models trained on organized datasets, especially in clinical diagnosis and disease categorization.

Among the most referenced models:

- Artificial Neural Networks (ANNs) manage extensive, unstructured data sets (e.g., social media, clinical text).
- Random Forests manage incomplete, noisy data for population-level risk predictions.
- Support Vector Machines (SVMs) offer high precision in binary classification for disease presence or absence.

These tools are central to forecasting epidemics, triaging high-risk populations, and tracking chronic diseases, showcasing AI's functional versatility.

Unsupervised and reinforcement learning also crop up but less so, predominantly in experimental settings (e.g., reinforcement learning for sepsis prediction). Limited general intelligence capability reinforces current constraints in reasoning and adaptability.
Whereas the hype over AI potential has been fed, public health AI today is characterized by pragmatically narrow-trained models. Strength is characterized by specificity and accuracy rather than reasoning or autonomy.

Theme 3: Expanding Applications in Public Health Practice

The literature indicates AI working on various layers of public health interventions:

- Disease Surveillance: Real-time detection of infections, for example, COVID-19, from live EHR feeds, internet activity, and environmental sensors.

- Predictive Analytics: Hybrid models combine clinical, environmental, and social data to predict outbreaks or hospital demand.
- Risk Stratification: IBM Watson type tools determine people at high risk for heart disease or diabetes with >90% accuracy.
- Spatial Modeling: GIS-AI integration enables geographic hotspots and resource allocation optimization.
- Precision Public Health: Tailored interventions for individuals or population segments based on genomic, behavioral, and environmental data.

These applications represent an integrated, system-wide reimagination of public health, in which interventions are no longer monolithic but context-sensitive, population-specific, and data-driven. AI's true strength lies in its versatility. By supporting granular, real-time insights, AI shifts public health from broad strategies to precision-targeted interventions.

Theme 4: Ethical Tensions and Trust Deficits

Ethical and legal concerns consistently surface in literature as major impediments to responsible AI adoption.

- Explainability and Trust: Many models are "black boxes," making it hard for clinicians to trust or interpret results. Explainable AI (XAI) is a possible solution.
- Data Bias and Consent: Inadequately curated data and murky consent processes create issues of privacy, autonomy, and discrimination.
- Dual-Use Dilemmas: Public good AI applications (e.g., disease prediction) might be redirected for surveillance or business use. (e.g., non-consensual surveillance).

- Human Oversight: Experts caution against unfettered trust in AI outputs and recommend ongoing human-in-the-loop systems for clinical and public health decision-making.

Ethics is not an add-on with AI its core. Transparency, cross-disciplinary governance, and crucial human involvement at every stage are necessary for responsible AI.

Theme 5: Infrastructure and Inequity - Double-Edged Potential

A common conflict is the duplicity of AI both a unifier and a divider. On the one side, AI enables mobile diagnosis, telemedicine, and mental health chatbots in developing areas. On the other, low data literacy, digital inequality, and infrastructure voids delay access to such technologies.

- Digital divide: Low-resource environments do not have internet, computational resources, and technical skills required for AI.
- Dataset bias: Biased predictions and misdiagnosis can occur if minority groups and low income populations are underrepresented in datasets.
- Telehealth disparity: Access in remote areas can be enhanced through mobile health applications, but they are only helpful if digital literacy and infrastructure are there.

Poor network connectivity, underrepresented training data, and unequal distribution of AI tools are the major threats to equity. These can be addressed if AI helps in decreasing instead of increasing health disparities.

CHAPTER 5 DISCUSSION

This chapter frames the themes that emerged during the literature review not just as descriptive results but as dynamic trends challenging prevailing models of epidemiology, risk regulation, and digital equality.

5.1 Reactive Surveillance to Predictive Intelligence: Promise versus Preparedness

While AI systems such as BlueDot and HealthMap have obvious speed and scale advantages, effectiveness in response to events such as COVID-19 also revealed institutional delay in responding to such lead indicators. This poses a vital gap: preparedness of institutions lagging behind technological readiness.

Although early outbreak signatures can be identified by applying prediction tools, absent prior governance procedures and trust arrangements, on-time intervention is limited. A number of studies considered mirrored this trade-off highlighting the fact that AI does not necessarily equate to enhanced health outcomes unless accompanied by policy responsiveness and interdisciplinarity coordination. The lack of prediction leading to action is an indication of a broader deficit in health systems agility rather than merely computational power.

5.2 Dominance of Narrow AI: Practical Strengths, Strategic Limits

The staggering dependence upon Artificial Narrow Intelligence (ANI) implies a practical tendency: public health is presently more effectively served by task-specialized models (e.g., for detecting outbreaks, classifying) than by generalizable reasoning. It is sound methodology but indicates a strategic weakness.

Few examined model robustness to new pathogens or changing social circumstances—eliciting worry that narrow AI, though accurate, might be fragile in unstructured, high-rate-of-change environments. Supervised learning, for example, excels with labeled data, while new disease warning signs tend to be unlabeled, equivocal, or socially filtered (e.g., pandemic misinformation). Inadequate application of unsupervised and reinforcement learning implies a lost potential for building stronger, adaptive systems that can learn in the presence of uncertainty and feedback.

This constraint also reflects a more profound challenge overfitting models to past patterns can diminish their capacity for predicting truly novel dangers. Accordingly, while tools based on ANI are operationally strong, their deployment must be accompanied by approaches that advance contextual awareness and flexibility.

5.3 Systemic Innovation: From Vertical Health Systems to Integrated Intelligence

Thematic implications indicate that AI is not only revolutionizing technical processes but also the structural reasoning of public health. Technologies such as GIS-based spatial models, risk stratification platforms, and individualized disease predictions all point towards a transition from vertical, disease-specific interventions to networked, precision-based health systems.

Yet, this revolution is not even. The majority of successful case studies (e.g., BlueDot, IBM Watson) are from high-income environments with dense data ecosystems and high digital literacy levels. Few studies examined the cost, training, or governance demands to implement these systems in regions with limited resources. A new type of health inequity is formed: algorithmic advantage where infrastructure is present, possibly expanding the digital divide.

Thus, as AI provides system-level power, its application needs to be sociotechnically anchored. Without distributed digital infrastructure, interoperable pipelines of data, and local contextualization, even the most precise models will fall short or get misused.

5.4 Ethical Disruption: Data Justice, Opacity, and Power Imbalances

Ethical conflicts are not marginal they are at the very heart of AI in public health. The ubiquity of black-box models contradicts clinical transparency, eroding trust and accountability. While Explainable AI (XAI) has been proposed as a solution, its use is still partial and mostly incapable of narrowing epistemic divides between AI engineers and healthcare practitioners.

Representativeness of data is another major problem. Datasets used in AI training typically lack low-income, minority, or rural patients and therefore allow for systematic underdiagnosis or misclassification. In addition, dual-use dangers are in the balance. Outbreak detection technologies produced for this purpose could be repurposed for applications in state or surveillance capitalism intrusion, especially under crisis circumstances, where information exchange is hastened. Scholarship frequently downplays the danger pointing out a normative blind spot in current AI-health scholarship: neglecting structural power inequalities when imagining good purpose.

These challenges highlight the mandates of algorithmic accountability mechanisms that guarantee AI based systems used for public health adhere to democratic norms, informed consent, and equitable access

5.5 AI and Equity: Between Empowerment and Exclusion

Perhaps the most paradoxical finding is AI’s simultaneous potential to both reduce and reinforce health inequity. On one hand, AI applications like mobile diagnostics, telehealth, and mental health bots expand reach to underserved populations. On the other, low digital literacy, poor connectivity, and algorithmic bias remain formidable barriers in LMICs and marginalized groups even in high-income countries.

Few of these studies mentioned "access" and none disassemble what equitable access looks like culturally adapted interfaces, local language NLP solutions, or participatory design with affected communities. Such omission risks repeating techno-solutionist "solutions" which fail under actual use.

To counter this, the future of AI in public health needs to take a capability-oriented approach to posing not only what can AI do, but who gains, under what circumstances, and at what costs.

CHAPTER 6
CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

This dissertation explored the application of Artificial Intelligence (AI) in population health, with a focus on its use in disease surveillance and prediction. Through a secondary thematic review of the literature, five core themes emerged: the evolution of surveillance systems, typologies of AI models, expanding real-world applications, ethical and legal challenges, and the infrastructural and equity-related implications of AI deployment.

The findings affirm that AI technologies especially machine learning, natural language processing, and deep learning are reshaping how health systems detect and manage disease threats. Tools like BlueDot and IBM Watson exemplify AI's potential to support early warning systems, individualized risk prediction, and precision-targeted interventions. However, the transformative promise of AI is tempered by unresolved challenges, including model transparency, data quality and representativeness, algorithmic bias, infrastructure gaps, and governance deficits.

Significantly, although AI has been considerably successful in technical implementation, its uptake into health systems is uneven especially across low-resource environments. Lacking simultaneous development in digital infrastructure, ethical guidance, and workforce skills, AI instruments will perpetuate current health inequities.

Finally, it is determined that AI is not a neutral technology. Its application in public health needs to be steered by the spirit of equity, transparency, contextual flexibility, and human control. AI can be an empowering tool but only if the development and deployment of AI are socially responsible and ethically grounded.

6.2 IMPLICATIONS

a. For Public Health Systems

- AI has the potential to move disease surveillance from reactive to proactive models, enhancing early detection and resource planning.
- Health systems need to invest in interoperable data infrastructure to maximize AI potential.
- National and regional public health governments need to create AI-readiness roadmaps, incorporating technical, ethical, and logistical factors.

b. For AI Developers and Data Scientists

- Explainable models (XAI) that can be interpreted by clinicians and public health workers are acutely needed.
- Developers need to focus on bias reduction, inclusive datasets, and culturally responsive model creation to allow generalizability across groups.
- End-users should be co-designing future systems, particularly in low- and middle-income contexts.

c. For Policymakers and Regulators

- Strong AI governance laws need to be implemented, with focus on privacy, consent, prevention of dual-use, and algorithmic accountability.
- There is a need for global coordination (e.g., WHO, EU AI Act) to align on ethical standards across borders.

- Support funding open-source public health AI tools for adaptation and transparency.

This research highlights that the future of public health is inextricable from the future of AI. As we are at the nexus of disease and data, it is not sufficient to create smart machines we have to create smart systems that benefit the public. That will take a convergence of technology, ethics, and governance coordinating with one another so as to advance AI that not only improves science, but health equity and social justice

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