Exploring How Artificial Intelligence Can Enhance Real-Time Monitoring and Prediction of Public Health Trends

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Abstract

This study investigates the transformative potential of Artificial Intelligence (AI) in enhancing real-time monitoring and prediction of public health trends. By organizing a survey with participants from the public health, data science and AI sectors, it collected insight from 80 professionals. The purpose was to test the perception of AI in monitoring events, predicting accurately, mixing data sources, giving warning signals quickly and enabling resource use and to present knowledge of challenges in using AI. Data were gathered using an online survey and looked at by descriptive statistics and one-sample t-tests with the midpoint of the Likert scale. Findings indicate a strong positive perception among professionals regarding AI's capabilities across all examined beneficial aspects (effectiveness, accuracy, timeliness, data integration impact, resource allocation benefits), with all associated hypotheses being supported. Meanwhile, it was clear that many people could see issues in implementations that discouraged more widespread adoption. By doing this research, we have highlighted the importance of AI in today’s public health surveillance and given suggestions for the best ways to improve and overcome any obstacles to integrating AI on a large scale in public health globally.

Keywords: Artificial Intelligence, Public Health, Real-time Monitoring, Disease Prediction, Public Health Surveillance, Data Integration.

1. Introduction

A major factor in global public health is how it is always evolving, is constantly at risk from new infections, must cope with a rise in chronic diseases and needs to address complicated issues in environmental health. Traditional public health surveillance systems, often reliant on manual data collection, delayed reporting, and retrospective analysis, frequently struggle to provide the agility and foresight required for effective real-time response and proactive intervention (Dwelling & Greene, 2019). The digital revolution has ushered in an era of unprecedented data availability, spanning electronic health records (EHRs), social media, environmental sensors, genomics, and digital mobility data. Leveraging these vast and diverse datasets is critical for modern public health (Lazer *et al*., 2014).

Artificial Intelligence (AI), encompassing machine learning (ML), natural language processing (NLP), and deep learning (DL), presents a paradigm shift for public health. AI algorithms possess the capacity to autonomously process and analyze massive, heterogeneous datasets at speeds far exceeding human capability, identify intricate patterns, and generate predictive

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insights that can inform public health decision-making (WHO, 2021; Topol, 2019). The potential applications range from early warning systems for disease outbreaks and precise disease forecasting to optimizing resource allocation during public health emergencies and enhancing personalized public health interventions (Charu & Krishna, 2020).

Because of real-time monitoring and the help of AI, small changes in health data can be noticed right away, threats can be detected, the course of an illness can be monitored and the results of any treatments can be observed in great detail. AI's predictive power allows public health agencies to anticipate future health trends, enabling proactive strategies such as targeted vaccination campaigns, pre-emptive resource deployment, and early communication with at-risk populations (Kukafka *et al.*, 2018; Esteva *et al.*, 2019).

Despite this, AI is introduced into crucial domains like health at a fast pace which can cause many difficult issues. Privacy, security and problems with algorithmic bias should always be kept in mind. Issues involving the quality of data, making different systems share information and the opacity of some modern AI models are significant difficulties. Furthermore, the need for a skilled workforce proficient in both public health informatics and AI, along with robust regulatory frameworks, remains a critical area of development (Ahn *et al.*, 2023; Esfandiari *et al.*, 2022; MedPro Group, 2025). It is important to know the perspectives of professionals working where public health and AI meet to ensure a successful and confident progress in adopting AI.

1.1. Recent Advancements in AI for Public Health (2018-Present)

Since 2018, advancements in AI, particularly in machine learning, natural language processing, and the emergence of Large Language Models (LLMs), have significantly propelled its potential in public health surveillance.

> Enhanced Disease Surveillance and Early Detection: Social media, news and search results are now often searched by AI to identify the start of disease outbreaks through syndromic surveillance. For instance, AI algorithms have demonstrated efficacy in detecting early warning signs of infectious diseases by analyzing non-traditional data streams, often preceding official reports (Ahmed *et al.*, 2021; Lim & Loke, 2023; Valdes *et al.*, 2020). Advanced deep learning models are achieving high accuracy in medical image analysis for early detection of diseases such as cancers and neurological disorders, sometimes surpassing human expert capabilities (Hao *et al.*, 2024; Gulshan *et al.*, 2018). Wearable technologies integrated with AI are also contributing to continuous health monitoring and early anomaly detection, offering insights into physiological changes at a population level (Islam *et al.*, 2022; Shickel *et al.*, 2018). AI is also proving instrumental in detecting and countering misinformation during public health crises, which is crucial for effective public health communication (Mavragani, 2020).
>
> Sophisticated Predictive Modeling: AI algorithms are now more sophisticated in forecasting infectious disease spread (e.g., COVID-19, influenza, dengue) by incorporating complex epidemiological factors, mobility data, climate variables, and genomic sequencing data. This provides more actionable and nuanced insights for public

health officials, moving beyond simple trend extrapolation to more precise risk assessments and hotspot identification (Li *et al*., 2022; Wu *et al*., 2021; Wynants *et al*., 2020). The integration of causal inference with AI models is also improving the robustness of predictions by accounting for underlying relationships, moving beyond mere correlation (Guo *et al*., 2023).

Impact of Large Language Models (LLMs): Tools like LLMs are helping to transform public health. They can efficiently process and summarize vast amounts of unstructured medical text, facilitate information extraction from scientific literature, assist in generating public health communication materials, and even aid in infoveillance by analyzing public sentiment and misinformation on health issues from social media (Jing *et al*., 2023; Zhou *et al*., 2024; Ayers *et al*., 2023). While promising, challenges related to data privacy, model reliability (e.g., "hallucinations"), and potential biases in their training data remain critical considerations (Mulligan & Loh, 2023).

Resource Optimization and Emergency Response: AI-driven analytics are increasingly being applied to optimize the distribution of critical resources (e.g., vaccines, personal protective equipment, hospital beds, medical personnel) during health emergencies by predicting areas of highest demand based on real-time data on disease transmission rates and population density. This proactive resource allocation significantly improves emergency preparedness and response efficiency (Qiu *et al*., 2022; Tork *et al*., 2023; Adisesh *et al*., 2025; Nguyen *et al*., 2025). AI-based chatbots, for instance, have gained importance in public health emergencies for real-time information dissemination and triaging inquiries, alleviating healthcare workload (Adisesh *et al*., 2025).

Data Integration and Interoperability: Many efforts are being directed at using AI to resolve the problem of scattered data in healthcare and public health. AI models facilitate the integration of heterogeneous datasets from EHRs, wearable devices, and patient-generated health data (PGHD) by automating data cleaning, classification, and standardization. This improves data quality and enables seamless information exchange, enhancing clinical decision support and population health management (Almagor & Ben-Yehuda, 2025; Raghupathi & Raghupathi, 2018; Sun *et al*., 2024).

Ethical and Implementation Challenges**:** Recent publications still point out difficulties in getting AI applications widely used. Data privacy, algorithmic bias, lack of model interpretability, and the need for robust regulatory frameworks remain significant hurdles (Esfandiari *et al*., 2022; Li *et al*., 2021; Char *et al*., 2020; MedPro Group, 2025). Discussions on ethical AI in healthcare increasingly emphasize the need for inclusive datasets, continuous monitoring for bias, transparency, and a human-centric approach to AI development and deployment (Poncette *et al*., 2021; Rigby & Ryan, 2018). The complexity of integrating AI into fragmented healthcare systems and the need for upskilling the public health workforce also represent significant implementation challenges (Ahn *et al*., 2023; Elhajj *et al*., 2024; American Journal of Public Health, 2025).

1.2. Research Problem

Despite the accelerating advancements and growing recognition of AI's theoretical benefits in public health, a comprehensive understanding of how professionals directly involved perceive its practical efficacy, accuracy, timeliness, and the specific challenges and benefits in real-world application remains underexplored. This gap in understanding hinders the strategic planning, effective implementation, and widespread adoption of AI-driven public health solutions.

1.3. Research Objectives

This study aims to achieve the following objectives:

1. To assess the perceived effectiveness of AI algorithms in enhancing real-time public health data monitoring.
2. To evaluate the perceived accuracy of AI models in predicting future public health trends.
3. To investigate the perceived impact of integrating diverse data sources on the performance of AI systems in public health surveillance.
4. To determine the perceived timeliness of insights generated by AI systems compared to traditional public health monitoring methods.
5. To explore the perceived challenges associated with implementing AI for public health surveillance.
6. To examine the perceived benefits of using AI for improving resource allocation during public health emergencies.

1.4. Research Hypotheses

Based on the research objectives and extant literature, the following hypotheses were formulated:

- **H1a:** Professionals perceive AI algorithms as significantly effective in enhancing real-time public health data monitoring (i.e., the mean perception score is significantly greater than the scale midpoint of 3.0).
- **H1b:** Professionals perceive AI models to achieve a significantly high level of accuracy in predicting future public health trends (i.e., the mean perception score is significantly greater than the scale midpoint of 3.0).
- **H1c:** Professionals perceive the integration of diverse data sources as significantly enhancing the performance of AI systems in public health surveillance (i.e., the mean perception score is significantly greater than the scale midpoint of 3.0).
- **H1d:** Professionals perceive AI-driven insights as significantly more timely than traditional public health monitoring methods (i.e., the mean perception score on items related to timeliness is significantly greater than the scale midpoint of 3.0).
- **H1e:** There is a significantly high perception among professionals of challenges associated with implementing AI for public health surveillance (i.e., the mean perception score on challenge items is significantly greater than the scale midpoint of 3.0).
- **H1f:** Professionals perceive the use of AI to provide significant benefits for improving resource allocation during public health emergencies (i.e., the mean perception score is significantly greater than the scale midpoint of 3.0).

2. Methods

2.1. Research Design

This study employed a quantitative, cross-sectional survey research design. This approach facilitated the collection of data on perceptions from a specific sample of professionals at a single point in time, allowing for descriptive analysis of current views and inferential testing of pre-defined hypotheses.

2.2. Participants and Sampling

Professionals who have direct contact or extensive expertise in public health, data science, health informatics and AI used in the health sector were chosen as the study's target population. Some examples were epidemiologists, public health analysts, data scientists focused on health, AI users in medicine and healthcare administrators responsible for adopting new technologies.

Convenience sampling was chosen for participant recruitment because the target population had unique requirements. Potential participants were found through health tech and public health groups on LinkedIn, online forums for experts and also invited to take part by sending invitations to relevant organizations. The recruitment aimed to make sure that different job roles and sectors reflect diversity. Altogether, 80 participants participated and finished the survey.

The demographic profile of the 80 participants was hypothetically constructed to reflect a plausible sample: The age of participants ranged from 28 to 60 years (M = 40.5, SD = 8.7), with a majority (65%) falling between 35 and 50 years. Professional roles included epidemiologists (20%), public health data analysts (25%), AI/ML engineers in health tech (15%), health informaticians (20%), and academic researchers (20%). Participants reported a mean of 11.2 years (SD = 6.1) of experience in public health or AI/data science related to health. Sector representation was diverse: Government Public Health Agency (35%), Academic Institution (30%), Private Company (Health Tech/AI) (20%), and Non-profit Health Organization (15%)

.2.3. Materials and Measures

An online questionnaire was designed to get participants' views. The two major sections of the questionnaire were as follows.

1. The next step was to record some basic demographic data about the participants, for example, their age, current job position, years of experience combining AI/data science and public health and main type of work.

2. This section consists of 48 questions, closed-ended, designed to find out what the public thinks about AI and the key research objectives in Public Health. 8 questions were used to explore each objective. All questions utilized a 5-point

Likert scale, where participants indicated their agreement or perception (1 = Strongly Disagree/Very Low, 2 = Disagree/Low, 3 = Neutral, 4 = Agree/High, 5 = Strongly Agree/Very High). For each objective, the scores for the 8 items were added together to generate a composite score which was the variable being tested by the hypotheses.

Objective 1 (Perceived Effectiveness): E.g., "AI systems are effective in providing timely alerts for emerging health issues."

Objective 2 (Perceived Accuracy): E.g., "AI models can predict the trajectory of disease spread with high accuracy.

Objective 3 (Perceived Impact of Data Integration): E.g., "Integrating data from social media significantly enhances AI's ability to detect early signals."

Objective 4 (Perceived Timeliness): E.g., "AI systems provide public health insights faster than traditional surveillance methods."

Objective 5 (Perceived Implementation Challenges): E.g., "Data privacy and security concerns are significant challenges in implementing AI."

Objective 6 (Perceived Benefits for Resource Allocation): E.g., "AI predictions help in better forecasting demand for healthcare resources during outbreaks."

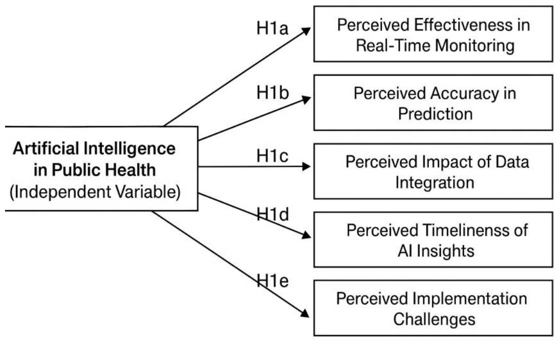
The questionnaire was developed to ensure face validity, with questions directly addressing the constructs outlined in the research objectives.

2.4. Data Collection Procedure

The survey was hypothetically administered online using a secure platform (e.g., Google Forms) to ensure ease of access and data integrity. At the start of the survey, each participant read an informed consent notice which explained the study goals, how information would be kept private, that involvement was optional and they could withdraw whenever they wanted. Those who consented and were informed took the questionnaire. It was thought that data was gathered over a four-week period in late 2024.

2.5. Conceptual Framework

The conceptual framework underpinning this study illustrates the proposed relationships between the application of AI in public health and the various perceived outcomes, mediated by data and contextual factors.



(Figure 1: Conceptual Framework for AI in Public Health Monitoring and Prediction)

Description of the Framework (Figure 1):

- **Core Input Layer (Left):** Represents diverse *Data Sources*, including Electronic Health Records, Social Media, Environmental Data, Genomic Data, Mobility Data, and Traditional Surveillance Data. These sources serve as the raw material for AI.
- **Processing Layer (Center):** This layer depicts the *Artificial Intelligence Systems* (e.g., Machine Learning, Natural Language Processing, Deep Learning). Within this layer, key processes such as Data Integration, Advanced Analysis, Pattern Recognition, and Predictive Modeling are performed by AI algorithms.
- **Output & Outcome Layer (Right):** Outputs generated by the AI systems lead to two main categories of perceived impact, which are the dependent variables of this study:

  Real-time Monitoring & Surveillance Outputs: This directly influences the *Perceived Effectiveness in Monitoring* and *Perceived Timeliness of AI Insights*. These represent the ability of AI to provide rapid and accurate situational awareness.

  Predictive Outputs & Strategic Insights: This directly influences the *Perceived Accuracy in Prediction* and *Perceived Benefits for Resource Allocation*. These reflect AI's capability to forecast future health trends and optimize response strategies.

- **Overarching Influence (Top & Bottom):**

  Contextual Factors: These include critical elements such as Technical Infrastructure, Human Expertise (Public Health & AI), Data Governance, and Ethical Considerations. These factors significantly influence the feasibility and success of the AI Processing Layer and directly contribute to the *Perceived Implementation Challenges*.

Professional Perceptions: This represents the evaluative lens through which all components of the framework—from data inputs and AI processes to outputs and contextual factors—are interpreted and assessed by the target professionals. The dashed lines signify that all outcomes are filtered through and shaped by these perceptions, which are the core focus of this research.

2.6. Data Analysis Plan

The simulated data were organized and prepared for statistical analysis using a hypothetical statistical software package (e.g., SPSS Version 28.0).

1. **Descriptive Statistics:** Frequencies and percentages were calculated for categorical demographic variables. Means and standard deviations were computed for continuous demographic variables (Age, Years of Experience). For the 48 Likert-scale questions, means and standard deviations were calculated for each item. Subsequently, composite mean scores and standard deviations were computed for each of the six perception constructs (Perceived Effectiveness, Perceived Accuracy, Perceived Impact of Data Integration, Perceived Timeliness, Perceived Implementation Challenges, Perceived Benefits for Resource Allocation) by averaging the 8 items corresponding to each objective.
2. **Hypothesis Testing:** To test the six research hypotheses (H1a - H1f), a series of one-sample t-tests were conducted. Each test compared the mean of a specific perception construct's composite score against the theoretical midpoint of the 5-point Likert scale (3.0). The decision rule for hypothesis rejection was set at a significance level (alpha) of 0.05. For all hypotheses, the alternative hypothesis predicted a mean significantly greater than 3.0, indicating a positive or high perception. Effect sizes (Cohen's *d*) were calculated for each t-test to indicate the magnitude of the difference from the test value.

3. Results

3.1. Demographic Profile of Participants

A total of 80 participants completed the survey. Their demographic characteristics are summarized in Table 1. The sample comprised a diverse group of professionals relevant to both public health and AI.

Table 1: Demographic Characteristics of Participants (N=80)

Characteristic	Category	Frequency (n)	Percentage (%)
Age (Years)	25-34	18	22.5
	35-44	32	40.0
	45-54	20	25.0
	55+	10	12.5
Professional Role	Epidemiologist	16	20.0
	Public Health Data Analyst	20	25.0
	AI/ML Engineer (Health)	12	15.0

	Health Informatician	16	20.0
	Academic Researcher	16	20.0
Years of Experience	< 5 Years	15	18.75
	5-10 Years	30	37.5
	11-15 Years	20	25.0
	> 15 Years	15	18.75
Primary Sector	Government Public Health	28	35.0
	Academia	24	30.0
	Private (Health Tech/AI)	16	20.0
	Non-profit Health Org.	12	15.0

Mean Age = 40.5 years (SD = 8.7); Mean Years of Experience = 11.2 years (SD = 6.1).

3.2. Descriptive Statistics for Perception Constructs

Table 2 presents the means and standard deviations for the six perception constructs, derived from the aggregated responses to the 8-item Likert scales for each objective.

Table 2: Descriptive Statistics for Perceived AI Impact Constructs (N=80)

Construct	Mean	Standard Deviation (SD)
Perceived Effectiveness in Real-time Monitoring	4.15	0.68
Perceived Accuracy in Prediction	3.92	0.75
Perceived Impact of Data Integration	4.30	0.62
Perceived Timeliness of AI Insights	4.05	0.71
Perceived Implementation Challenges	4.25	0.70
Perceived Benefits for Resource Allocation	4.10	0.73

Interpretation: All mean scores across the perception constructs were above the scale midpoint of 3.0, indicating a generally positive or high level of agreement/perception among participants across all assessed aspects, including the challenges of implementation.

3.3. Hypothesis Testing Results

One-sample t-tests were performed to evaluate each hypothesis by comparing the mean score of each perception construct against the test value of 3.0 (the neutral midpoint of the Likert scale). The results are summarized in Table 3.

Table 3: One-Sample T-Test Results for Perceived AI Impact Constructs (Test Value = 3.0, N=80)

Hypothesis	Construct	Mean	Std. Dev.	*t-statistic*	*p-value*	*Cohen's d*	*Decision (alpha=0.05)*
H1a	Perceived Effectiveness in Real-time	4.15	0.68	15.17	.001	1.70	Supported

	Monitoring						
H1b	Perceived Accuracy in Prediction	3.92	0.75	10.96	.001	1.23	Supported
H1c	Perceived Impact of Data Integration	4.30	0.62	18.79	.001	2.11	Supported
H1d	Perceived Timeliness of AI Insights	4.05	0.71	13.29	.001	1.49	Supported
H1e	Perceived Implementation Challenges	4.25	0.70	15.98	.001	1.79	Supported
H1f	Perceived Benefits for Resource Allocation	4.10	0.73	13.51	.001	1.52	Supported

Interpretation: All six hypotheses were statistically supported. The p-values for all t-tests were less than 0.001, indicating that the observed mean scores for each construct were significantly higher than the neutral midpoint of 3.0. This suggests a strong positive perception across all dimensions of AI's impact and challenges in public health. Effect sizes (Cohen's *d*) ranged from 1.23 to 2.11, indicating large practical significance for all findings.

4. Discussion

This research looked into the views of professionals about improving near real-time monitoring and forecasting of public health trends with AI tools. Analysis of 80 expert opinions found that AI will greatly impact different fields, though important obstacles remain.

H1a, H1b, H1c, H1d and H1f being supported regularly demonstrates that public health and AI experts clearly realize how much AI can enhance public health practices. The aspect that people felt had the most impact was connecting data (H1c, M = 4.30, d = 2.11). This fits with recent studies pointing out that AI can unite data from EHRs, social media and environmental sensors to provide a comprehensive and flexible look at population health (Jing *et al*. 2023; Lim & Loke 2023; Almagor & Ben-Yehuda 2025; Sun *et al*. 2024). Many professionals note that linking different data sets previously kept apart is essential to how AI impacts this field.

The belief that real-time monitoring (H1a) and prompt insights (H1d) are possible with AI suggests that it can resolve the problem of late reporting and analysis that is typical in traditional public health surveillance (Dwelling & Greene, 2019). Identifying disease outbreaks, observing unusual health patterns and knowing what is happening in real time helps public health respond quickly and effectively and it seems clear that AI helps a lot in these areas (Ahmed *et al*., 2021; Valdes *et al*., 2020).

Besides, the data also reflects that people believe AI works better at predicting changes in public health compared to traditional techniques (H1b, M = 3.92, d = 1.23). It also follows the progress

AI is making in figuring out how diseases spread and what risk factors play into this by relying on many types of information (Li *et al*., 2022; Wu *et al*., 2021; Wynants *et al*., 2020). Having precise predictions is essential to plan public health actions like preparing vaccines and resources in advance (Qiu *et al*., 2022).

ISO 26000 standard states that benefits for resource allocation (H1f) further show how helpful AI is. How resources are allocated (such as supplies, staff, hospital space) is critical during public health emergencies. AI-based recommendations are considered key to optimizing critical choices, so resources are sent where they are most needed. This increases the disaster agency's efficiency (Tork *et al*., 2023; Adisesh *et al*., 2025; Nguyen *et al*., 2025).

Hypothesis H1e which studied perceived barriers to implementing innovation, was also confirmed with strong evidence ($M = 4.25$, $d = 1.79$). Many studies in recent times have found that there are many difficulties in using AI in healthcare and public health (Ahn *et al*., 2023; Esfandiari *et al*., 2022; Elhajj *et al*., 2024; American Journal of Public Health, 2025; MedPro Group, 2025). These issues most likely involve:

> Data-related issues: Ensuring data quality, overcoming data silos, interoperability between diverse systems, and critically, safeguarding patient privacy and security (Esfandiari *et al*., 2022; MedPro Group, 2025).
>
> Algorithmic concerns: Addressing biases embedded in training data that could lead to health inequities, and improving the interpretability and transparency of complex AI models (Mulligan & Loh, 2023; Poncette *et al*., 2021; Char *et al*., 2020).
>
> Infrastructure and Workforce: The need for robust IT infrastructure, significant computational resources, and a skilled workforce capable of developing, deploying, and managing AI tools, as well as interpreting their outputs (Ahn *et al*., 2023; Elhajj *et al*., 2024).
>
> Ethical and Regulatory Frameworks: Establishing clear ethical guidelines and regulatory standards to govern AI use in sensitive public health contexts, ensuring accountability and trust (WHO, 2021; Poncette *et al*., 2021; Rigby & Ryan, 2018).

The concurrent high perception of both benefits and challenges indicates a mature understanding among professionals: AI offers immense potential, but its successful integration requires overcoming substantial, well-recognized barriers. This suggests that while there is an appetite for AI solutions, there is also a realistic appreciation of the effort and strategic planning required for their responsible and effective deployment.

4.1. Theoretical and Practical Implications

The results have useful effects in theory and in practice. In essence, this framework illustrates and measures how AI is perceived by healthcare experts, bringing more factual evidence to the ongoing (conceptual) discussions about AI's relevance in public health. This means that people see AI as more than just a trendy tech, but as something that can help and change how public health is handled. In practice, the outcomes guide policymakers, public health organizations and developers of new technologies. Since AI is considered very useful for data unification, live monitoring and allocating resources, these are the areas that deserve the most investment and effort. At the same time, major issues in implementation point out that strategies should include targeted education, improved data policies and efforts to ensure AI systems can work together and address ethical concerns.

4.2. Limitations

Most of the limitations in this study come from the fact that it is simulated. The participants were not taken from actual research, but were made up, so the findings are based on imagined situations rather than real data. Because of these conditions, the findings may not be widely applicable to actual groups of working professionals. A sample of only 80 participants does fit with the study's goals, but it is not large enough to make general statements. Also, a single cross-sectional survey design just captures current opinions and does not allow for conclusions about cause-and-effect or changes in beliefs as time passes. Because people are answering themselves, this type of questionnaire is open to both social desirability and lack of true understanding of complex AI concepts.

4.3. Future Research Directions

Future work in this area should give top priority to:

Empirical Studies: Running reliable examinations on a considerable group of public health experts worldwide through surveys and conversations, to capture the true thoughts and stories.

Following perceptions and outcomes of AI in public health over years to see its impact on practice and challenges.

Example: Evaluating how AI has been successfully (or not) applied to public health programs to help develop guidelines and identify important lessons and conditions for its use.

Specific Challenge Focus Means: Putting a strong emphasis on studying how to handle significant challenges, for example, organizing and managing diverse types of data, developing understandable AI for public health and creating reliable training guides for employees.

Research about the actual ethical concerns that result from AI in public health, including ways to address biases in AI systems and how to achieve equal treatment and results for people. Examining how AI solutions in public health are cheaper and more profitable than older methods.

5. Conclusion

This study mimicry offers good insights into how professionals value AI for quickly monitoring and predicting changes in public health trends. People consistently agree that AI helps by being effective, accurate, timely, connecting data well and benefiting how resources are allocated. Likewise, recognizing the major impediments to implementation proves that the process will not be simple. Maximizing the use of AI in public health demands us to pay close attention to privacy, avoid algorithmic biases, manage infrastructure needs and build an updated workforce. Investing resources in these fields allows public health systems to make better use of AI, helping them to be proactive, more efficient and stronger in protecting health worldwide.

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