

# Leveraging AI-Driven Predictive Analytics to Strengthen Health System Resilience Against Climate-Related Patient Surges and Infrastructure Strain

Jalene Jacob

Industry Professional, Millennium Medical Network

DOI: <https://doi.org/10.51244/IJRSI.2025.1215000135P>

Received: 22 August 2025; Accepted: 27 August 2025; Published: 27 September 2025

## ABSTRACT

Climate change, including heatwaves, flooding, and wildfire smoke exposure, is driving more frequent and severe health catastrophes, generating sudden patient surges that place considerable strain on critical hospital and healthcare infrastructure. Traditional preparedness approaches are limited by retrospective data and static protocols. This review synthesizes evidence on the role of artificial intelligence (AI)-driven predictive analytics in strengthening health system resilience to these climate-related stressors. I examine methodologies that integrate clinical, environmental, and social vulnerability data to forecast patient demand, enable proactive resource allocation, and optimize infrastructure readiness. Current applications demonstrate potential to enhance early warning systems, improve surge capacity planning, and inform strategic decision-making. However, challenges remain including fragmented data systems, algorithmic bias, privacy concerns, and limited interoperability. Importantly, without deliberate policy and governance frameworks, AI deployment risks exacerbating inequities, particularly in low-resourced health systems. I argue that harnessing AI for climate resilience requires coordinated investment in data infrastructure, ethical oversight, and cross-sector partnerships. If implemented thoughtfully, AI predictive analytics can help shift health system preparedness from reactive crisis response to proactive climate adaptation.

**Keywords:** Artificial Intelligence, predictive analytics, health system resilience, climate change, patient surges, infrastructure strain, public health, disaster preparedness.

## INTRODUCTION

Statistical records indicate that the ten hottest years on record occurred between 2013 and 2022, highlighting the urgent need to address urban heat [1]. Climate change is one of the most pressing public health challenges of the 21st century [21]. Rising global temperatures, more frequent and severe heatwaves, floods, wildfires, droughts, and shifting patterns of vector-borne diseases are directly affecting human health, leading to unprecedented demands on healthcare systems [14].

In Europe, climate change has already influenced the transmission of numerous vector-borne diseases and is expected to continue doing so in the coming decades [20]. According to [20], this has been linked to the observed expansion of ticks to higher altitudes and latitudes, notably the *Ixodes ricinus* specie, a vector for Lyme borreliosis and tick-borne encephalitis. These climate-related health crises produce acute patient surges that overwhelm emergency departments, deplete supplies, and strain healthcare personnel [13]. At the same time, hospitals, clinics, and supply chains often sustain direct damage and disruption, undermining their ability to deliver essential services [19].

Traditional reactive approaches to disaster management are increasingly insufficient to address the scale and complexity of these challenges. Proactive, data-driven strategies are needed to help health systems anticipate, prepare for, and respond effectively to evolving climate-related threats [23]. Artificial intelligence (AI), particularly AI-driven predictive analytics, offers a promising approach. By integrating clinical, environmental

and demographic data, predictive analytics can identify emerging patterns and forecast demand surges with greater precision, enabling earlier intervention and more efficient allocation of resources [6].

This review examines how AI-driven predictive analytics can help strengthen health system resilience against climate-related patient surges and infrastructure strain. It evaluates current applications and evidence, highlights opportunities for proactive planning, and analyses the challenges of data quality, interoperability, ethics, and equity. The article aims to inform health policy and system leaders on how AI can support a shift from reactive crisis management to proactive climate adaptation.

## **METHODS**

This literature review was conducted through a search of academic databases and online repositories to identify relevant peer-reviewed articles. The search strategy was ensured a comprehensive and reproducible approach to gathering evidence on how AI-driven predictive analytics can strengthen health system resilience against climate-related patient surges and infrastructure strain.

### **Search Strategy**

A systematic search was performed across four key academic databases: PubMed, Scopus, Web of Science, and Google Scholar. The search was conducted using a combination of keywords and their synonyms, linked with Boolean operators (AND, OR). The search terms included “Artificial Intelligence,” “machine learning,” “predictive analytics,” “healthcare,” “climate change,” “patient surge,” “hospital capacity,” and “infrastructure strain.”

The search was limited to peer-reviewed journal articles, conference proceedings, and reputable reports published in English from January 2012 to August 2025, to ensure the inclusion of recent technological advancements and climate science.

### **Study Selection and Screening Process**

The initial search yielded over 200,000 results, that was then narrowed down to 1,254 articles. A screening process was then applied to filter for the most relevant research.

All titles and abstracts were screened to exclude studies that were irrelevant (e.g., focused solely on climate mitigation, not AI-driven, or not related to health systems). This stage resulted in 135 articles selected for text review. These articles were then assessed against predefined inclusion and exclusion criteria.

### **Inclusion Criteria**

Eligible studies focused on the applications of AI or predictive analytics in healthcare or public health contexts related to climate change impacts, with particular attention to patient surges, infrastructure resilience, resource allocation, or early warning systems.

### **Exclusion Criteria**

Editorials, commentaries, non-research opinion pieces, and articles that did not directly link AI with both health system resilience and climate impacts were excluded.

### **Final Selection**

This rigorous process led to the final inclusion of 25 articles in the review. The reference lists of these articles were also manually scanned to identify additional relevant publications, a method known as "snowballing."

While restricting to English-language publications may have excluded some perspectives, this approach ensured a focused, up-to-date synthesis of the literature most relevant to health policy and systems planning in both developed and developing countries.

## Data Extraction and Synthesis

Data was extracted from the final set of articles. The extracted information included study type (e.g., case study, systematic review, pilot project, large-scale model); AI methodology used (e.g., machine learning, deep learning, geospatial analysis); climate hazard addressed (e.g., heatwaves, floods, air pollution); health system component impacted (e.g., emergency department, infrastructure, supply chain); key findings, including quantitative metrics (if available) and qualitative observations; identified limitations and challenges.

The evidence was synthesized through a thematic analysis. Instead of simply aggregating results, the review focused on identifying recurring themes and patterns across the studies. Findings were compared and critically evaluated to identify consistent trends, conflicting results, and areas of consensus or debate. The "effectiveness" of AI was assessed not only through quantitative outcomes (e.g., model accuracy) but also through a critical evaluation of the scalability and long-term viability of the proposed solutions, as highlighted in the discussion and conclusion sections. Claims about AI's benefits were consistently contextualized by the identified limitations and challenges, ensuring a balanced and realistic assessment.

## FINDINGS

The results reveal that AI-driven predictive analytics hold significant promise for strengthening climate-resilient health systems by enhancing foresight, improving operational efficiency, and supporting evidence-based decision-making. Across the literature, AI applications were consistently linked to optimized resource allocation, early warning capabilities, and adaptive supply chain management, particularly in contexts of extreme weather events and patient surges. At the same time, studies highlight critical over-arching limitations such as data quality, algorithmic bias, and interoperability challenges which place constraints on anticipated benefits and underscore the need for robust governance frameworks. Collectively, these findings suggest that while AI is not a total solution, it can serve as a powerful enhancer of resilience if deployed with attention to technical rigor, ethical safeguards, and equitable access.

### Predicting Patient Surges Exacerbated by Climate

AI applications show strong potential for anticipating climate-sensitive health events, particularly asthma exacerbations, cardiovascular strain, and heat-related illnesses. Through machine learning algorithms, predictive models and real-time data from Internet of Things (IoT)-based sensors systems can analyze environmental exposures alongside clinical records to flag patients at elevated risk. Reference [17] for example, demonstrates that integrating local air quality data with patient histories enables early prediction of asthma exacerbations and reduces reliance on emergency services. Similarly, reference [24] found that deep learning models which analyze meteorological and pollution patterns achieve high accuracy in forecasting hospital admissions for respiratory disease during severe heat and smog events. These approaches provide not only patient-level benefits such as targeted outreach and personalized treatment plans, but also system-level advantages, including reduced emergency visits and lower costs of care. However, much of this evidence remains pilot-stage, with limited long-term evaluation of cost-effectiveness across diverse health systems.

### Optimization of Resource Allocation and Supply Chain Management

Climate change intensifies strain on health system infrastructure, particularly during extreme weather events that disrupt supply chains. AI-enabled optimization models offer a solution by aligning inventory, logistics, and workforce deployment with predicted demand surges. AI holds substantial potential to transform supply chain management by enabling more accurate demand forecasting, optimizing transport routes, and managing inventories in ways that reduce emissions and conserve resources [4].

Case studies outlined in references [11] and [12] show that predictive analytics can anticipate medicine shortages during heatwaves and floods, while reinforcement learning algorithms dynamically reallocate supplies to the most affected facilities. Likewise, IoT-linked distribution systems enhance visibility of stock levels across regions, ensuring timely resupply of critical items like asthma inhalers and vaccines. This reduces waste, prevents bottlenecks, and supports equity by directing resources toward vulnerable populations. Importantly,

while simulation studies suggest substantial gains in efficiency and cost savings, few large-scale implementations exist, and broader adoption will require cross-sector collaboration and integration with existing health logistics systems.

### **Early Warning Systems and Disaster Preparedness**

AI is increasingly central to climate disaster preparation, with predictive tools helping anticipate floods, hurricanes, and vector-borne disease outbreaks. For example, the United Nations Climate Change [22] report highlights the use of satellite data combined with machine learning to map flood risk zones and trigger early alerts for hospitals in low-lying areas. In the public health domain, ensemble models analyzing rainfall, temperature, and mosquito population dynamics have shown effectiveness in predicting dengue and malaria outbreaks weeks in advance, thus allowing pre-emptive community interventions. These early warning systems strengthen resilience by enabling hospitals and emergency response teams to pre-position supplies, allocate staff, and expand surge capacity. Yet challenges remain in ensuring interoperability between climate models, health data, and local infrastructure, particularly in resource-constrained settings.

### **Policy Implications**

Across these domains, AI has demonstrated clear potential to enhance climate-health resilience by predicting demand surges, optimizing resources, and strengthening preparedness. The evidence suggests three policy-relevant implications:

#### **Targeted Investments in Predictive Infrastructure**

Scaling successful pilots will require investment in interoperable data systems that integrate environmental, clinical, and logistics information.

#### **Equity-Centered Deployment**

AI-enabled optimization should prioritize underserved populations who bear disproportionate climate-related health risks.

#### **Governance and Evaluation Frameworks**

Rigorous assessment of AI tools covering effectiveness, cost-benefit, and ethical considerations, is essential before widespread adoption.

Overall, while AI has not yet reached full operational maturity in this domain, it provides a credible pathway for health systems to anticipate, adapt, and respond more effectively to the health impacts of climate change.

### **Limitations**

Despite promising applications, several limitations temper the scalability and reliability of AI in climate-health adaptation. These include:

#### **Data Quality and Availability**

AI models depend on large, high-quality datasets, yet many health systems, particularly in low- and middle-income countries, lack reliable clinical, environmental, or logistical data. Missing data, underreporting, and fragmented systems can compromise predictive accuracy. In many LMICs, data poverty is a pervasive issue. Health data is often fragmented, incomplete, or recorded on paper, making it difficult to digitize and standardize. Essential environmental data from weather stations, air quality sensors, and satellite imagery may be sparse or non-existent [22]. This lack of comprehensive, high-quality data creates a fundamental barrier as AI models trained on such limited information may produce unreliable or biased predictions. Furthermore, if data is not representative of all populations, the resulting AI models could perpetuate or even exacerbate existing health inequities by systematically underestimating risks in certain communities.

## **The Digital Divide**

The digital divide represents a critical gap between countries and communities with and without access to information and communication technologies. While high-income countries invest in 5G networks and cloud computing, many regions in LMICs still lack basic internet access and the digital literacy necessary to utilize AI tools [22]. This creates a bifurcated system where advanced, AI-driven solutions are only accessible to a select few, leaving the most vulnerable populations without the benefits of proactive healthcare planning. This divide also extends to the human capital needed to operate and maintain these systems.

A lack of trained data scientists, public health informaticians, and healthcare professionals familiar with AI tools can make it impossible to deploy and sustain these technologies at a meaningful scale. Without addressing this fundamental gap in access and expertise, AI solutions risk widening, rather than closing the global health equity gap.

## **Algorithm and Equity Bias**

Models trained in data from resource rich regions may not generalize to diverse populations, reinforcing existing inequities. Without deliberate bias audits and inclusive training datasets, AI could systematically underperform and underestimate risks for vulnerable groups. Overfitting is a significant challenge in AI modelling, arising when a model memorizes training data to the extent that it performs poorly on new, unseen inputs [5]. Mitigating this issue requires carefully balancing model complexity to enhance generalization.

## **Interpretability and Infrastructure Gaps**

Integrating AI outputs into existing health information systems is challenging. Dissimilar data standards, weak digital infrastructure, and lack of technical capacity hinder seamless adoption, particularly in resource-constrained settings. As such, climate change poses a dual threat to health systems in LMICs by simultaneously increasing health risks and threatening the very infrastructure needed to respond. Many healthcare facilities and essential services in these regions are already grappling with infrastructural fragility and hospitals may lack reliable electricity, internet connectivity, or robust cooling systems, making them highly susceptible to power outages and damage from extreme weather events like floods or cyclones. Even the most accurate AI prediction of a patient surge is useless if the hospital's power grid fails, its digital systems are offline, or its supply chain is cut off due to damaged roads. The very systems AI relies on for data transmission and real-time communication are often the first to fail during a crisis.

## **Trust and Governance Barriers**

Policymakers and health leaders may hesitate to act on AI-driven predictions without transparent methods and clear accountability frameworks. A lack of explainability reduces trust among clinicians and decision-makers.

## **Sustainability and Cost Considerations**

While pilot projects often show success, maintaining AI tools requires ongoing investment in hardware, software, and human expertise. Many systems may find this unsustainable without dedicated funding and policy support.

Recognizing and addressing these multi-dimensional challenges is critical to ensure AI contributes to equitable and resilient health system adaptation rather than exacerbating vulnerabilities.

## **DISCUSSION**

The evidence suggests that AI-driven predictive analytics is a powerful and increasingly indispensable tool for strengthening health system resilience against the escalating threats posed by climate-related patient surges and infrastructure strain. AI-based approaches can improve early warning systems and allocate resources more efficiently through the analysis of large, heterogeneous data sets and the ability to recognize complex patterns [2].



By offering unprecedented capabilities in forecasting, optimization, and early warning, AI transforms health systems from reactive entities into proactive, adaptive, and robust responders to climate impacts. The ability to anticipate where and when patient surges will occur, identify vulnerable infrastructure, and strategically allocate resources represents a paradigm shift in disaster preparedness and public health management.

The applications highlighted in this study, from predicting heatwave-related illnesses and vector-borne disease outbreaks to optimizing medical supply chains and assessing infrastructure vulnerability, all demonstrate the wide-ranging utility of AI. These applications enable health systems to undertake crucial pre-emptive measures such as adjusting staffing levels, pre-positioning medical supplies, issuing targeted public health warnings, and fortifying critical infrastructure. This proactive approach not only saves lives and reduces morbidity, but also minimizes the economic burden associated with large-scale climate disasters.

Despite the compelling promise, the widespread adoption and effective implementation of AI in this domain are not without challenges. A few of these areas are highlighted below.

### **Data Quality, Availability, and Interoperability**

It cannot be overstated that AI models are only as good as the data they are trained on. A significant challenge lies in the availability of comprehensive, high-quality, and standardized environmental, health, and socio-demographic data [7]. Data systems across different agencies and jurisdictions, coupled with varying data collection methods and formats, hinder the seamless integration required for robust AI models. Establishing interoperable data platforms and promoting data sharing agreements are critical next steps [10].

### **Bias and Ethical Considerations**

The use of AI in healthcare raises profound ethical concerns, particularly regarding data privacy, algorithmic bias, and equitable access [15]. AI models, if trained on biased historical data, can perpetuate or even exacerbate existing health inequalities, potentially disadvantageous to vulnerable populations. Transparency, explainability, and fairness in AI algorithms are paramount to build trust among healthcare professionals and the public [9]. In [9], it is emphasized that Robust guidelines and regulatory frameworks are essential to ensure that AI solutions are developed and deployed responsibly.

Bias can creep into models at multiple stages: in the data collection phase, if certain populations are underrepresented in health records or environmental data; in the algorithm design, if the model's objective function prioritizes overall accuracy at the expense of performance for minority groups; and in the implementation phase, if the insights are not applied equitably across different communities.

To mitigate this, a proactive approach to algorithmic fairness is required. This involves:

#### **Fairness Audits**

Regularly auditing AI models to test for discriminatory outcomes across different demographic groups (e.g., based on race, gender, socioeconomic status, or location).

#### **Representational Data**

Actively working to gather and incorporate more diverse and representative datasets from underserved populations to ensure models are trained on a comprehensive view of reality.

#### **Value-Sensitive Design**

Integrating ethical principles directly into the design process of AI systems. This means prioritizing outcomes like equity and fairness alongside technical metrics like accuracy.

Furthermore, a global health ethics framework for AI must consider:

## Capacity Building

Invest in local expertise and infrastructure in Low- and Middle-Income Countries (LMICs) rather than simply importing finished AI products from developed states. This includes training data scientists, public health professionals, and AI experts in these regions.

## Open-Source and Low-Cost Solutions

Prioritize the development of open-source AI tools and models that can be adapted and run on low-cost decentralized systems, making them more accessible to resource-constrained environments.

## Context-Specific Design

Recognize that AI models developed for high-income countries may not be relevant or effective in different cultural, social, and environmental contexts. Therefore, solutions should be designed to fit the unique characteristics of local communities.

## International Collaboration

Fostering partnerships and knowledge sharing between countries to ensure that the benefits of AI are shared globally, and that risks are managed collectively is essential to the sustainable AI infrastructure.

By integrating these ethical considerations into every stage of development and deployment, AI can be a powerful force for a more resilient and equitable global health system in the face of aggressive climate change. Developers can work toward creating AI systems that not only predict patient surges but do so in a way that provides equitable benefits to all, especially the most vulnerable populations.

## Computational Resources and Infrastructure

Training and deploying sophisticated AI models, specifically deep learning networks, require significant computational power and robust digital infrastructure. This can be a substantial barrier for low-resource settings, potentially widening the digital divide in climate resilience efforts [22]. Investment in sustainable computing solutions and localized capacity building are vital.

## Human-AI Collaboration and Workforce Development

AI is a tool to augment human decision-making, not replace it. Therefore, effective integration requires healthcare professionals to understand AI's capabilities and its limitations. A recent report by PricewaterhouseCoopers [16] on *'The future of care'* highlights that employers should concentrate on creating novel employment models that both incentivize and motivate their workforce, noting that upskilling serves as an equally strong motivator. The report emphasizes that training programs are needed to equip the healthcare workforce with the necessary skills to interact with and interpret AI-generated insights. In essence, building trust and ensuring that AI outputs are explainable and actionable are crucial for successful adoption.

## Regulatory and Policy Frameworks

The rapidly evolving nature of AI necessitates agile and responsive regulatory frameworks that can keep pace with technological advancements while ensuring safety, efficacy, and ethical deployment. Policies that incentivize research and development, facilitate data sharing, and address liability issues will be essential.

Looking forward, several opportunities exist to advance the role of AI in climate-resilient health systems:

## Integration of Multi-Modal Data

Future research should focus on integrating diverse data streams including satellite imagery, social media data,

genomic information and traditional health records to build more comprehensive and accurate predictive models.

### **Explainable AI (XAI)**

Developing more transparent and interpretable AI models will enhance trust and facilitate adoption by clinicians and public health practitioners.

### **Edge AI and Decentralized Systems**

Exploring edge computing and decentralized AI approaches can enable real-time data processing and decision-making in remote or resource-limited environments, enhancing resilience where it's most needed.

### **Climate-Health System Digital Twins**

Developing digital twins of health systems that integrate real-time data with AI models could create dynamic simulation environments with predictions for scenario planning and testing of climate resilience strategies [3].

### **Global Collaboration and Open Science**

Fostering international collaboration and promoting open-source AI tools and datasets can accelerate progress and ensure that these powerful technologies benefit all regions, particularly those most vulnerable to climate change.

### **Humanitarian Healthcare**

Artificial Intelligence (AI) is transforming humanitarian healthcare by providing innovative solutions to critical challenges in crisis response [8]. By fostering collaboration among governments, NGOs, and technology providers, AI can serve as a powerful catalyst for strengthening humanitarian healthcare systems, enhancing resilience and efficiency, and delivering better outcomes for vulnerable populations during crises. [8]. In addition to AI-powered warning systems, prominent applications include AI-powered chatbots and telemedicine platforms for pre-hospital or out-patient care and monitoring [8].

## **CONCLUSION**

With the global population surpassing 8 billion, 4.5 billion of whom live in urban areas, rapid urbanization has intensified a range of environmental and ecological challenges, most notably the Urban Heat Island (UHI) effect [1].

AI-driven predictive analytics presents a transformative opportunity to enhance health system resilience in the face of climate change, offering capabilities to anticipate patient surges, optimize supply chains, and strengthen infrastructure and public health preparedness.

Evidence from diverse studies demonstrates that machine learning and deep learning models, particularly when integrated with real-time environmental and clinical data, can accurately forecast climate-sensitive health events such as heat-related illnesses, vector-borne disease outbreaks, and respiratory exacerbations, enabling pre-emptive staffing, resource allocation, and community-level interventions. These tools also support dynamic supply chain management, risk mapping, and early warning systems, allowing health systems to shift from reactive to proactive responses while minimizing morbidity, mortality, and economic burden. Despite this promise, challenges including uneven data quality, algorithmic bias, interoperability gaps, limited infrastructure, and workforce capacity constraints must be addressed to ensure equitable and responsible deployment.

Strategic investments in interoperable data systems, ethical governance, workforce training, and policy frameworks are critical to translating AI innovation into tangible resilience gains, particularly for vulnerable populations and resource-limited settings. By embedding AI within robust governance and operational strategies, healthcare systems can not only respond more effectively to climate-related shocks but also build sustainable,



adaptive, and globally equitable models of care.

## REFERENCES

1. Ali Najah Ahmed, Nouar AlDahoul, Nurhanani A. Aziz, Y.F. Huang, Mohsen Sherif, Ahmed El-Shafie. The urban heat Island effect: A review on predictive approaches using artificial intelligence models. *City and Environment Interactions*. Volume 28, 2025. 100234. ISSN 2590-2520.
2. Andrae, S., Tariq, M., & Sergio, R. (2025). Artificial Intelligence in Disaster Management: Sustainable Response and Recovery. In *Cases on AI-Driven Solutions to Environmental Challenges* (Vol. Chapter 4, pp. 73–144). essay, IGI Global Scientific Publishing.
3. Chaparro-Cárdenas, S. L., Ramirez-Bautista, J. A., Terven, J., Córdova-Esparza, D. M., Romero-Gonzalez, J. A., Ramírez-Pedraza, A., & Chavez-Urbiola, E. A. (2025). A Technological Review of Digital Twins and Artificial Intelligence for Personalized and Predictive Healthcare. *Healthcare (Basel, Switzerland)*, 13(14), 1763. <https://doi.org/10.3390/healthcare13141763>
4. Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial Intelligence in Logistics Optimization with Sustainable Criteria: A Review. *Sustainability*, 16(21), 9145. <https://doi.org/10.3390/su16219145>
5. David B. Olawade, Ojima Z. Wada, Abimbola O. Ige, Bamise I. Egbewole, Adedayo Olojo, Bankole I. Oladapo. Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. *Hygiene and Environmental Health Advances*, Volume 12, 2024. 100114. ISSN 2773-0492. <https://doi.org/10.1016/j.heha.2024.100114>.
6. Dixon, D., Sattar, H., Moros, N., Kesireddy, S. R., Ahsan, H., Lakkimsetti, M., Fatima, M., Doshi, D., Sadhu, K., & Junaid Hassan, M. (2024). Unveiling the Influence of AI Predictive Analytics on Patient Outcomes: A Comprehensive Narrative Review. *Cureus*, 16(5), e59954. <https://doi.org/10.7759/cureus.59954>
7. Ganatra, S., Khadke, S., Kumar, A., Khan, S., Javed, Z., Nasir, K., Rajagopalan, S., Wadhera, R. K., Dani, S. S., & Al-Kindi, S. (2024). Standardizing social determinants of health data: a proposal for a comprehensive screening tool to address health equity a systematic review. *Health Affairs Scholar*, 2(12), qxae151. <https://doi.org/10.1093/haschl/qxae151>
8. Haykal, D., Goldust, M., Cartier, H., & Treacy, P. (2025). AI in humanitarian healthcare: a game changer for crisis response. *Frontiers in Artificial Intelligence*, 8, 1627773. <https://doi.org/10.3389/frai.2025.1627773>
9. Kiseleva, A., Kotzinos, D., & De Hert, P. (2022). Transparency of AI in Healthcare as a Multilayered System of Accountabilities: Between Legal Requirements and Technical Limitations. *Frontiers in Artificial Intelligence*, 5, 879603. <https://doi.org/10.3389/frai.2022.879603>
10. Li, L., Back, E., Lee, S., Shipley, R., Mapitse, N., Elbe, S., Smallman, M., Wilson, J., Yasin, I., Rees, G., Gordon, B., Murray, V., Roberts, S. L., Cupani, A., & Kostkova, P. (2025). Balancing Risks and Opportunities: Data-Empowered-Health Ecosystems. *Journal of Medical Internet Research*, 27, e57237. <https://doi.org/10.2196/57237>
11. Marchese, K., & Phillips, F.-K. (2025). AI for Infrastructure Resilience: Deloitte Global. Deloitte. <https://www.deloitte.com/global/en/issues/climate/ai-for-infrastructure-resilience.html>
12. NVL Suvarchala Reddy, M. Ganga Raju, Nisha Shri C., N. Maheswari, D. Krishnaveni, P. Saritha. (2025). From Pollution to Prediction: The Role of Air pollution and Artificial intelligence in Asthma. *International Journal of Scientific Research and Technology*, 2(6), 164–171. <https://doi.org/10.5281/zenodo.15582272>
13. Paganini M, Lamine H, Della Corte F, Hubloue I, Ragazzoni L, Barone-Adesi F. Factors causing emergency medical care overload during heatwaves: A Delphi study. *PLoS One*. 2023 Dec 20;18(12):e0295128. doi: 10.1371/journal.pone.0295128. PMID: 38117826; PMCID: PMC10732456.
14. Parums D. V. (2024). A Review of the Increasing Global Impact of Climate Change on Human Health and Approaches to Medical Preparedness. *Medical science monitor: international medical journal of experimental and clinical research*, 30, e945763. <https://doi.org/10.12659/MSM.945763>
15. [15]. Pham T. (2025). Ethical and legal considerations in healthcare AI: innovation and policy for safe and fair use. *Royal Society Open Science*, 12(5), 241873. <https://doi.org/10.1098/rsos.241873>

16. PricewaterhouseCoopers. (2025). The Future of Care. PwC. <https://www.pwc.com/gx/en/issues/business-model-reinvention/how-we-care-for-ourselves/future-of-care-healthcare-ecosystem.html>
17. Ram, S., Zhang, W., Williams, M., & Pengetnze, Y. (2015). Predicting asthma-related emergency department visits using big data. *IEEE Journal of Biomedical and Health Informatics*, 19(4), 1216–1223. <https://doi.org/10.1109/JBHI.2015.2404829>
18. Saha, R., Shofiullah, S., Faysal, S A., & Happy, A. T. (2024). Systematic Literature Review on Artificial Intelligence Applications in Supply Chain Demand Forecasting. *Academic Journal on Business Administration, Innovation & Sustainability*, 4. 109-127. 10.69593/ajbais.v4i04.136.
19. Salam, A., Wireko, A. A., Jiffry, R., Ng, J. C., Patel, H., Zahid, M. J., Mehta, A., Huang, H., Abdul-Rahman, T., & Isik, A. (2023). The impact of natural disasters on healthcare and surgical services in low- and middle-income countries. *Annals of Medicine and Surgery* (2012), 85(8), 3774–3777. <https://doi.org/10.1097/MS9.0000000000001041>
20. Semenza, J. C., & Suk, J. E. (2018). Vector-borne diseases and climate change: a European perspective. *FEMS Microbiology Letters*, 365(2), fnx244. <https://doi.org/10.1093/femsle/fnx244>
21. Siqueira, C. E. (2024, September 19). Is climate change the most important public health challenge of the 21st century? Main. [https://www.jblearning.com/blog/jbl/2024/09/19/is-climate-change-the-most-important-public-health-challenge-of-the-21st-century?srsId=AfmBOooW28d8KvaQeEWwYzcPGvIk\\_f5y9fUTf5btszTgHRG0LnQzepys](https://www.jblearning.com/blog/jbl/2024/09/19/is-climate-change-the-most-important-public-health-challenge-of-the-21st-century?srsId=AfmBOooW28d8KvaQeEWwYzcPGvIk_f5y9fUTf5btszTgHRG0LnQzepys)
22. United Nations Climate Change (UNFCCC). (2025). AI and Climate Action: Opportunities, Risks and Challenges for Developing Countries. [unfccc.int](https://unfccc.int/news/ai-and-climate-action-opportunities-risks-and-challenges-for-developing-countries). <https://unfccc.int/news/ai-and-climate-action-opportunities-risks-and-challenges-for-developing-countries>
23. Villanueva-Miranda, I., Xiao, G., & Xie, Y. (2025). Artificial intelligence in early warning systems for infectious disease surveillance: a systematic review. *Frontiers in Public Health*, 13, 1609615. <https://doi.org/10.3389/fpubh.2025.1609615>
24. Xu, H., Guo, S., Shi, X., Wu, Y., Pan, J., Gao, H., Tang, Y., & Han, A. (2024). Machine learning-based analysis and prediction of meteorological factors and urban heatstroke diseases. *Frontiers in Public Health*.12, 2296-2565. <https://doi.org/10.3389/fpubh.2024.1420608>
25. Ye, Y., Pandey, A., Bawden, C. et al. Integrating artificial intelligence with mechanistic epidemiological modeling: a scoping review of opportunities and challenges. *Nat Commun* 16, 581 (2025). <https://doi.org/10.1038/s41467-024-55461-x>