Volume 4, Issue 5, 2026

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

AI-INTEGRATED PHARMACOVIGILANCE AND CLIMATE-SENSITIVE DISEASE SURVEILLANCE FOR PEDIATRIC POPULATIONS IN URBAN PAKISTAN

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DOI: https://doi.org/10.5281/zenodo.20117872

Keywords
Artificial Intelligence; Pharmacovigilance; Climate-Sensitive Diseases; Pediatric Health; Disease Surveillance; Explainable AI (XAI); Machine Learning; Public Health Informatics; Urban Pakistan; Predictive Healthcare Systems.

Article History
Received: 14 March 2026
Accepted: 22 April 2026
Published: 11 May 2026

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Abstract
The increasing burden of pediatric health risks in urban Pakistan, driven by climate variability, infectious disease outbreaks, and adverse drug reactions (ADRs), necessitates advanced and integrated surveillance systems. Traditional pharmacovigilance and disease surveillance mechanisms remain fragmented, reactive, and insufficient for real-time decision-making. This study proposes an AI-Integrated Pharmacovigilance and Climate-Sensitive Disease Surveillance Framework designed to enhance early detection, prediction accuracy, and interpretability of pediatric health risks. The framework integrates heterogeneous data sources, including clinical records, pharmacovigilance reports, and environmental indicators such as temperature, humidity, rainfall, and air pollution. Machine learning and deep learning techniques were applied for predictive modeling, while Explainable Artificial Intelligence (XAI) methods were incorporated to ensure transparency and interpretability of outcomes. The model was evaluated using performance metrics and expert validation. Results indicated that the proposed framework significantly outperformed baseline models in accuracy, precision, recall, and false-risk detection, while also demonstrating strong correlation between climate variables and disease incidence. Expert assessments confirmed high levels of trust, usability, and interpretability of the system. The study concludes that integrating AI with pharmacovigilance and climate-sensitive surveillance provides a robust, scalable, and transparent solution for strengthening pediatric healthcare systems in climate-vulnerable urban environments.

INTRODUCTION
The rapid convergence of Artificial Intelligence (AI), digital health systems, and climate variability has transformed global public health surveillance paradigms, particularly in rapidly urbanizing regions. In developing countries such as Pakistan, urban populations are increasingly exposed to complex health risks arising from infectious diseases, adverse drug reactions, environmental pollution, and climate-sensitive outbreaks. Pediatric populations are especially vulnerable due to physiological susceptibility, higher exposure to environmental hazards, and limited adaptive immunity. Consequently, there is a growing need for integrated, intelligent, and real-time surveillance systems capable of addressing both pharmacovigilance and climate-

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ISSN: (e) 3007-1607 (p) 3007-1593

sensitive disease dynamics in a unified framework.

Traditional pharmacovigilance systems in many low- and middle-income countries remain largely passive, relying on spontaneous reporting of adverse drug reactions (ADRs) from healthcare providers. These systems often suffer from underreporting, delayed signal detection, and limited analytical capacity, which restrict timely identification of drug safety risks in pediatric populations. Similarly, conventional disease surveillance systems depend on hospital records and laboratory confirmations, which are inherently retrospective and slow, limiting early outbreak detection. Recent evidence highlights that delays in surveillance reporting significantly reduce the effectiveness of public health interventions in urban environments where disease transmission is rapid and population density is high (Alwakeel, 2025; Jehajo et al., 2026).

The increasing availability of real-time digital data sources—such as electronic health records, pharmacy dispensing systems, environmental sensors, and social media analytics—has enabled the development of AI-driven surveillance systems. Machine learning and deep learning models have demonstrated strong capability in detecting anomalies, predicting disease outbreaks, and integrating multi-source health data for decision support. Studies indicate that AI-based surveillance frameworks can significantly improve early detection accuracy and reduce response time by analyzing structured and unstructured datasets simultaneously (Pant et al., 2025; Joshi et al., 2025). In particular, models such as Long Short-Term Memory (LSTM) networks and anomaly detection algorithms have shown high effectiveness in forecasting disease trends and identifying abnormal health patterns in real time.

Climate-sensitive diseases, including dengue, malaria, diarrheal infections, and respiratory illnesses, are increasingly influenced by environmental factors such as temperature variation, humidity, rainfall patterns, and urban flooding. Recent research highlights that integrating climate data with health surveillance systems enhances predictive accuracy and enables early warning of outbreak-prone conditions (Campbell et al., 2025). However, in Pakistan's urban settings, such integration remains limited due to fragmented data systems, weak interoperability between health and environmental databases, and insufficient deployment of advanced AI infrastructure. This gap is particularly critical for pediatric populations, where delayed detection of climate-induced disease outbreaks can result in severe morbidity and mortality.

Pharmacovigilance systems also face similar limitations in integrating environmental and clinical determinants of drug safety. Emerging evidence suggests that environmental stressors such as heatwaves and pollution may alter drug metabolism and increase the risk of adverse drug reactions in children. However, current monitoring systems do not account for these interactions, leading to incomplete safety assessments. AI-integrated pharmacovigilance frameworks offer the potential to bridge this gap by combining clinical data with environmental indicators to identify complex drug–environment–disease interactions in real time.

In Pakistan's urban healthcare landscape, the absence of integrated AI-based systems that simultaneously address pharmacovigilance and climate-sensitive disease surveillance represents a critical gap in pediatric healthcare protection. Existing surveillance mechanisms operate in silos, limiting their ability to provide comprehensive situational awareness or predictive insights. Therefore, there is a pressing need for a unified AI-integrated framework that combines predictive analytics, real-time monitoring, and explainable artificial intelligence to enhance early detection, improve clinical decision-making, and strengthen pediatric health resilience against evolving environmental and pharmaceutical risks.

Problem Statement

Urban Pakistan is experiencing a rapid rise in pediatric health vulnerabilities due to the combined impact of climate variability, infectious disease outbreaks, environmental pollution, and irrational or poorly monitored medication use. Despite the availability of healthcare data sources such as hospital records, pharmacy dispensing systems, and environmental monitoring networks, these systems operate in silos and lack integration. As a result, early warning capabilities for climate-sensitive diseases and adverse drug reactions (ADRs) remain weak, delayed, and largely reactive rather than predictive.

Pharmacovigilance systems in Pakistan are primarily manual and passive, relying on voluntary reporting of adverse drug reactions, which leads to significant underreporting, delayed detection, and limited analytical depth. At the same time, disease surveillance systems are not sufficiently integrated with environmental and climate data, making it difficult to anticipate outbreaks of dengue, diarrhea, respiratory infections, and other climate-sensitive diseases that disproportionately affect children. This fragmentation reduces the effectiveness of public health response mechanisms and limits the ability of healthcare authorities to implement timely interventions.

Furthermore, existing surveillance frameworks lack the capability to process large-scale, multi-source, real-time data generated from hospitals, pharmacies, meteorological systems, and digital health platforms. Although Artificial Intelligence (AI) and Machine Learning (ML) technologies have demonstrated strong potential in predictive analytics and anomaly detection, their application in integrated pharmacovigilance and climate-health surveillance remains limited in Pakistan. Additionally, most existing AI-based systems operate as “black-box” models, offering limited interpretability and reducing trust among healthcare professionals and decision-makers.

The absence of an integrated, explainable, and AI-driven surveillance framework that combines pharmacovigilance with climate-sensitive disease monitoring creates a critical gap in pediatric healthcare protection. This gap restricts early detection of drug-related risks, delays outbreak prediction, and weakens evidence-based decision-making in urban healthcare systems. Therefore, there is a pressing need to develop an AI-integrated, explainable, and real-time surveillance framework capable of improving pediatric health outcomes by enabling proactive detection of both adverse drug reactions and climate-sensitive disease outbreaks in urban Pakistan.

Research Questions

1. How can Artificial Intelligence be integrated with pharmacovigilance and climate-sensitive disease surveillance systems to improve pediatric healthcare outcomes in urban Pakistan?
2. What are the key limitations of existing pharmacovigilance and disease surveillance systems in detecting adverse drug reactions and climate-related disease outbreaks?
3. How effectively can AI-based models predict climate-sensitive disease patterns affecting pediatric populations in urban environments?
4. What role does Explainable Artificial Intelligence (XAI) play in improving transparency, trust, and decision-making in integrated health surveillance systems?
5. How can an AI-integrated surveillance framework enhance early warning capabilities for pediatric adverse drug reactions and climate-sensitive diseases?

Research Objectives

General Objective

To develop and evaluate an AI-integrated pharmacovigilance and climate-sensitive disease surveillance framework for improving pediatric healthcare outcomes in urban Pakistan.

Specific Objectives

1. To analyze the limitations of existing pharmacovigilance and disease surveillance systems in urban Pakistan.
2. To examine the relationship between climate variability, adverse drug reactions, and pediatric disease patterns.
3. To design an AI-based integrated framework for real-time detection of adverse drug reactions and climate-sensitive disease outbreaks.
4. To incorporate Explainable Artificial Intelligence (XAI) techniques to enhance transparency and interpretability of surveillance predictions.
5. To evaluate the effectiveness of the proposed framework in improving early warning accuracy and decision-making in pediatric healthcare systems.
6. To propose policy and operational recommendations for implementing AI-driven integrated surveillance systems in Pakistan’s urban healthcare infrastructure.

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Significance of the Study

This study is significant as it addresses a critical and emerging public health challenge in urban Pakistan, where pediatric populations are increasingly exposed to the combined risks of climate-sensitive diseases and adverse drug reactions (ADRs). The fragmentation of pharmacovigilance systems and disease surveillance mechanisms has limited the ability of healthcare institutions to generate timely, predictive, and actionable insights. By proposing an AI-integrated and explainable surveillance framework, this study contributes to strengthening early warning systems and improving pediatric healthcare outcomes in resource-constrained and high-risk urban environments.

From a theoretical perspective, the study extends the existing body of knowledge by integrating three important domains—pharmacovigilance, climate-sensitive disease surveillance, and Explainable Artificial Intelligence (XAI). It provides a multidisciplinary framework that enhances understanding of how AI can be effectively applied in healthcare monitoring systems while maintaining transparency and interpretability. This integration contributes to the advancement of health informatics and AI-driven public health surveillance literature, particularly in developing country contexts.

Practically, the study offers a scalable and intelligent solution for healthcare institutions, regulatory authorities, and public health organizations in Pakistan. The proposed framework enables real-time detection of adverse drug reactions and climate-related disease outbreaks by utilizing multi-source data, including hospital records, pharmaceutical data, and environmental indicators. This can significantly improve early diagnosis, reduce response time, and support evidence-based clinical and policy decisions. The inclusion of explainable AI further enhances trust and usability among healthcare professionals by making predictive outputs understandable and actionable.

For policymakers and public health authorities, the study provides valuable insights for developing integrated digital health strategies and strengthening national surveillance infrastructure. It highlights the importance of adopting AI-driven, data-centric approaches for managing pediatric health risks in the context of climate change and increasing urbanization. The findings can support the formulation of health policies that prioritize real-time monitoring, data interoperability, and predictive analytics in national healthcare systems.

Socially, the study is significant because improved surveillance and early detection systems can reduce morbidity and mortality among children, who are one of the most vulnerable population groups. By enabling timely intervention and improving healthcare responsiveness, the proposed framework has the potential to enhance public trust in digital health systems and contribute to healthier urban communities in Pakistan.

Literature Review

The increasing convergence of Artificial Intelligence (AI), healthcare informatics, and environmental monitoring has significantly transformed global public health surveillance systems. Recent literature emphasizes that traditional surveillance mechanisms in developing countries are often fragmented, reactive, and insufficient for addressing complex, multi-factorial health challenges such as adverse drug reactions (ADRs) and climate-sensitive disease outbreaks. In urban settings, particularly in low- and middle-income countries like Pakistan, the burden of pediatric diseases is further intensified by environmental pollution, climate variability, and weak pharmacovigilance infrastructure, necessitating the development of integrated and intelligent surveillance frameworks (Alwakeel, 2025; Jehajo et al., 2026).

Pharmacovigilance Systems and Their Limitations

Pharmacovigilance plays a critical role in ensuring drug safety by monitoring, detecting, and preventing adverse drug reactions. However, existing pharmacovigilance systems in many developing countries remain largely passive and rely on voluntary reporting mechanisms, which results in significant underreporting and delayed identification of drug safety signals. Studies indicate that traditional pharmacovigilance frameworks lack real-time analytical capabilities and are unable to process large-scale clinical and pharmaceutical data efficiently (Sarker, 2021). In pediatric populations, these limitations are

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more pronounced due to variations in drug metabolism, dosage sensitivity, and higher vulnerability to medication-related complications.

Climate-Sensitive Disease Surveillance

Climate change has emerged as a major driver of infectious and non-infectious disease patterns globally. Research highlights that variations in temperature, humidity, rainfall, and urban flooding significantly influence the transmission dynamics of diseases such as dengue, malaria, respiratory infections, and diarrheal diseases. Campbell et al. (2025) emphasized that pediatric populations are particularly vulnerable to climate-sensitive diseases due to physiological and environmental exposure factors. Similarly, IoT-enabled environmental monitoring systems have shown potential in predicting disease outbreaks by integrating meteorological and epidemiological data; however, such systems remain underutilized in urban healthcare infrastructures of Pakistan.

AI in Healthcare Surveillance Systems

Artificial Intelligence and Machine Learning (ML) have demonstrated significant potential in improving healthcare surveillance by enabling predictive analytics, anomaly detection, and real-time decision support. AI-based systems can process heterogeneous datasets, including electronic health records, pharmacy databases, environmental data, and social media signals, to identify early warning indicators of disease outbreaks and drug safety issues. Studies such as Pant et al. (2025) and Joshi et al. (2025) have shown that AI-driven health monitoring systems significantly improve detection accuracy and reduce response time in epidemic surveillance. Deep learning models such as Long Short-Term Memory (LSTM) networks and convolutional neural networks (CNNs) have been widely applied for temporal disease prediction and pattern recognition in healthcare datasets.

Integration of Pharmacovigilance and Disease Surveillance

Recent literature suggests a growing need for integrated health surveillance systems that combine pharmacovigilance with disease outbreak monitoring. However, most existing frameworks operate in isolation, limiting their ability to capture complex interactions between drug reactions and environmental factors. The integration of these systems is particularly important for pediatric populations, where drug-environment interactions may exacerbate health risks. Despite advancements in digital health technologies, limited research has focused on developing unified frameworks that simultaneously address drug safety and climate-sensitive disease dynamics in real time.

Role of Explainable Artificial Intelligence (XAI)

A major challenge in AI-driven healthcare systems is the "black-box" nature of predictive models, which limits transparency and trust among healthcare professionals. Explainable Artificial Intelligence (XAI) has emerged as a critical solution to address this limitation by providing interpretable and transparent model outputs. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) enable users to understand the contribution of different features in AI predictions. Research indicates that XAI improves clinical trust, enhances decision-making, and supports regulatory compliance in healthcare applications (Lundberg & Lee, 2017).

The reviewed literature reveals that while significant progress has been made in AI-based healthcare surveillance, there remains a lack of integrated frameworks that combine pharmacovigilance and climate-sensitive disease monitoring, particularly for pediatric populations in urban Pakistan. Furthermore, limited attention has been given to explainability in such integrated systems, which is essential for real-world adoption in healthcare environments. This gap highlights the need for an AI-integrated, explainable, and real-time surveillance framework capable of improving early detection, enhancing decision-making, and strengthening pediatric healthcare resilience in climate-vulnerable urban settings.

Underpinning Theory

Syndromic Surveillance Theory (Integrated Digital Public Health Surveillance Theory)

The present study is grounded in the Syndromic Surveillance Theory, which is widely used in modern public health informatics to enable early

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detection of disease outbreaks and health-related anomalies before formal clinical diagnoses are confirmed. This theory emphasizes the continuous, real-time collection, analysis, and interpretation of diverse health-related data sources to identify abnormal patterns that may indicate emerging public health threats. Unlike traditional surveillance systems that rely on laboratory-confirmed diagnoses, syndromic surveillance focuses on pre-diagnostic indicators such as clinical symptoms, pharmacy sales, hospital admissions, environmental conditions, and behavioral signals.

In the context of this study, the theory is extended into an AI-enhanced and integrated surveillance perspective, where Artificial Intelligence (AI) and Machine Learning (ML) techniques are applied to process large-scale heterogeneous datasets from pharmacovigilance systems, healthcare records, and climate monitoring platforms. This integration allows the system to detect both adverse drug reactions (ADRs) and climate-sensitive disease outbreaks in real time, particularly among vulnerable pediatric populations in urban environments.

A core principle of syndromic surveillance theory is early warning through pattern recognition, which aligns closely with AI-based predictive analytics. Machine learning models can identify subtle deviations from normal health patterns, while climate data integration enables the system to associate environmental changes with disease outbreaks. This makes the theory highly suitable for addressing the complex interaction between pharmacological effects and environmental determinants of health.

Furthermore, the theory supports data fusion across multiple domains, which is essential for this study's objective of integrating pharmacovigilance and climate-sensitive disease surveillance. By combining pharmaceutical data (drug usage and adverse reactions), clinical data (hospital records), and environmental data (temperature, humidity, rainfall, pollution), the system enhances situational awareness and predictive accuracy.

In addition, the incorporation of Explainable Artificial Intelligence (XAI) strengthens the applicability of syndromic surveillance theory by addressing one of its modern limitations—lack of interpretability in automated decision systems. XAI ensures that predictions generated by AI models are transparent and understandable to healthcare professionals, thereby improving trust, usability, and decision-making in real-world healthcare settings.

In summary, syndromic surveillance theory provides a strong conceptual foundation for this study by supporting early detection, multi-source data integration, and real-time health monitoring. When combined with AI and explainability techniques, it evolves into a powerful framework for proactive pediatric health surveillance in climate-vulnerable urban environments such as Pakistan.

Concise Hypotheses

H1: AI-integrated pharmacovigilance systems significantly improve the early detection of adverse drug reactions (ADRs) in pediatric populations compared to traditional pharmacovigilance systems.

H2: Climate-sensitive disease surveillance models enhanced with Artificial Intelligence significantly improve the prediction accuracy of pediatric disease outbreaks in urban Pakistan.

H3: There is a significant relationship between climate variability indicators (temperature, rainfall, humidity, pollution) and the incidence of pediatric climate-sensitive diseases.

H4: The integration of pharmacovigilance data and climate-sensitive surveillance data significantly enhances the accuracy of health risk prediction models.

H5: Explainable Artificial Intelligence (XAI) techniques significantly improve healthcare professionals' trust and interpretability of AI-based surveillance predictions.

H6: AI-integrated surveillance systems significantly reduce the response time for detecting pediatric health risks compared to conventional surveillance systems.

Methodology

Research Design

The study adopted a quantitative, design-based and simulation-oriented research approach to develop and evaluate an AI-Integrated Pharmacovigilance and Climate-Sensitive Disease Surveillance Framework for pediatric populations in urban Pakistan. An experimental research design was employed to assess the predictive performance, accuracy, and

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interpretability of the proposed model under different healthcare and environmental scenarios. The methodology was structured to ensure systematic integration of pharmacovigilance data, climate indicators, and machine learning-based predictive analytics.

Research Population

The population of the study comprised three main components: (i) pediatric health records from urban healthcare facilities in Pakistan, (ii) pharmacovigilance and adverse drug reaction (ADR) reporting data obtained from hospital and pharmaceutical databases, and (iii) climate and environmental datasets including temperature, humidity, rainfall, and air pollution indicators from urban monitoring stations. Additionally, healthcare professionals including pediatricians, pharmacists, epidemiologists, and public health experts were included as the human validation population for evaluating system usability and interpretability.

Sample Size

A total sample of 18,500 records was selected for model development and evaluation. This included approximately 10,000 pediatric clinical and pharmacovigilance records and 8,500 climate and environmental data entries representing urban regions of Pakistan. Furthermore, 150 healthcare professionals were selected as expert respondents using purposive sampling to evaluate the effectiveness, interpretability, and practical usability of the proposed framework.

Sampling Technique

The study applied a combination of stratified sampling and purposive sampling techniques. Stratified sampling was used to ensure balanced representation of different disease categories, climatic conditions, and adverse drug reaction types. Purposive sampling was used to select healthcare professionals with relevant experience in pediatrics, pharmacovigilance, and public health surveillance systems.

Data Collection

Data were collected from multiple secondary and primary sources. Secondary data included hospital electronic health records, pharmacovigilance databases, and publicly available climate datasets. Primary data were collected through structured questionnaires and evaluation forms administered to healthcare professionals. The data collection process ensured integration of clinical, pharmaceutical, and environmental variables to support AI-based modeling.

Model Development and Implementation

The proposed framework was developed using machine learning and deep learning techniques integrated with Explainable Artificial Intelligence (XAI). Data preprocessing techniques such as normalization, missing value handling, feature extraction, and dimensionality reduction were applied. Predictive models including Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks were implemented to analyze temporal disease patterns and drug safety signals. XAI techniques such as SHAP and LIME were integrated to ensure interpretability of model outputs.

Data Analysis Techniques

The data were analyzed using Python-based machine learning tools and statistical evaluation methods. Model performance was assessed using accuracy, precision, recall, F1-score, and area under the curve (AUC). Comparative analysis was conducted between traditional surveillance approaches and the proposed AI-integrated framework. Descriptive statistics and inferential analysis were used to interpret expert feedback regarding system usability, transparency, and reliability.

Ethical Considerations

The study ensured strict ethical compliance by using anonymized and de-identified datasets. No personal identifiers were retained during analysis. Permission was obtained for the use of institutional data, and confidentiality of healthcare professionals participating in the evaluation process was maintained throughout the study. The system was designed strictly for public health improvement and not for any commercial or non-ethical use.

Data Analysis

The data analysis was conducted to evaluate the performance of the proposed AI-Integrated

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Pharmacovigilance and Climate-Sensitive Disease Surveillance Framework for pediatric populations in urban Pakistan. The analysis involved quantitative model evaluation, comparative performance assessment with baseline models, and qualitative expert evaluation of system interpretability and usability. Machine learning performance metrics and statistical tools were used to ensure rigorous evaluation of predictive accuracy and system reliability.

Predictive Model Performance Analysis

The performance of the proposed framework was evaluated using standard classification metrics including Accuracy, Precision, Recall, F1-Score, and AUC-ROC. The results were compared with baseline models including Logistic Regression, Random Forest, and Long Short-Term Memory (LSTM).

Table 1: Comparative Performance of Predictive Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Logistic Regression	86.4	84.7	83.9	84.2	0.88
Random Forest	91.8	90.6	89.9	90.2	0.93
LSTM Model	93.7	92.9	92.4	92.6	0.95
Proposed AI-XAI Model	**97.9**	**97.3**	**96.8**	**97.0**	**0.98**

The results indicate that the proposed AI-integrated and explainable model significantly outperformed all baseline models across all evaluation metrics. The highest accuracy of 97.9% demonstrates the strong predictive capability of the framework in identifying pediatric health risks associated with both adverse drug reactions and climate-sensitive diseases. The improved AUC-ROC value (0.98) indicates excellent classification performance and high discriminative ability between normal and high-risk cases.

The reduction in error rates and improvement in F1-score further confirm that the model maintains a balanced performance between precision and recall. This is particularly important in healthcare applications where both false positives and false negatives can have serious consequences. The integration of climate and pharmacovigilance data contributed significantly to improving prediction reliability.

Disease Type Prediction Analysis

The framework was further evaluated across multiple pediatric disease categories influenced by climate variability and drug-related factors.

Table 2: Disease-Specific Prediction Accuracy

Disease Category	Detection Accuracy (%)
Dengue Fever	98.6
Respiratory Infections	97.4
Diarrheal Diseases	96.9
Heat-Related Illnesses	97.8
Adverse Drug Reactions (ADRs)	96.5

The results show consistently high detection accuracy across all disease categories. Dengue fever and heat-related illnesses achieved the highest predictive accuracy, reflecting strong model sensitivity to climate-driven health conditions. The slightly lower accuracy for adverse drug reactions suggests that pharmacovigilance data remains complex and heterogeneous, requiring further refinement in feature engineering. Overall, the framework demonstrated strong adaptability across both infectious and drug-related health risks.

Climate and Health Relationship Analysis

The relationship between climatic variables and pediatric disease incidence was analyzed using correlation-based statistical evaluation.

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Table 3: Correlation Between Climate Factors and Disease Incidence

Climate Variable	Correlation Coefficient (r)	Significance
Temperature	0.78	Strong
Humidity	0.72	Strong
Rainfall	0.81	Very Strong
Air Pollution (PM2.5)	0.76	Strong

The analysis revealed a strong positive correlation between climate variables and pediatric disease incidence. Rainfall showed the highest correlation (r = 0.81), indicating its significant role in triggering vector-borne and waterborne diseases. Temperature and air pollution also demonstrated strong associations with disease outbreaks. These findings confirm that climate variability is a major determinant of pediatric health risks in urban Pakistan and should be integrated into surveillance systems for accurate prediction.

Explainability and Expert Evaluation

The explainability performance of the framework was assessed using feedback from healthcare professionals, including pediatricians, pharmacists, and public health experts.

Table 4: Expert Evaluation of System Explainability

Evaluation Dimension	Mean Score (out of 5)	Standard Deviation
Interpretability	4.82	0.29
Transparency	4.86	0.24
Trust in System Output	4.79	0.31
Clinical Decision Support	4.75	0.33

The expert evaluation results indicate a high level of satisfaction with the explainability features of the proposed framework. Transparency received the highest mean score (4.86), indicating that healthcare professionals found the system's decision-making process highly understandable. The strong trust score (4.79) confirms that explainable outputs significantly improve confidence in AI-driven health surveillance systems. Additionally, high interpretability and decision support scores demonstrate that the framework is practically useful for clinical and public health decision-making.

The comprehensive data analysis confirms that the proposed AI-integrated and explainable surveillance framework significantly enhances predictive accuracy, early detection capability, and interpretability in pediatric healthcare monitoring. The integration of pharmacovigilance data with climate-sensitive indicators provides a more holistic and accurate understanding of health risks. Furthermore, the incorporation of Explainable Artificial Intelligence strengthens trust, usability, and clinical acceptance of the system. Overall, the findings demonstrate that AI-driven integrated surveillance systems offer a highly effective solution for improving pediatric health outcomes in climate-vulnerable urban environments such as Pakistan.

Discussion

The findings of this study demonstrate that the integration of Artificial Intelligence with pharmacovigilance and climate-sensitive disease surveillance significantly enhances the early detection and prediction of pediatric health risks in urban Pakistan. The proposed framework outperformed conventional statistical and standalone machine learning models in terms of accuracy, precision, recall, and overall predictive reliability. This improvement is primarily attributed to the fusion of heterogeneous datasets, including clinical records, adverse drug reaction reports, and environmental indicators such as temperature, rainfall, humidity, and air pollution.

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A key observation from the results is the strong relationship between climate variability and the incidence of pediatric diseases, particularly dengue fever, respiratory infections, and diarrheal diseases. This confirms that environmental factors play a critical role in shaping disease patterns in urban settings. The AI-based model successfully captured these nonlinear relationships, enabling more accurate forecasting of outbreaks. Furthermore, the integration of pharmacovigilance data allowed the system to identify potential adverse drug reactions in correlation with environmental stressors, which is a significant advancement over traditional surveillance systems.

The inclusion of Explainable Artificial Intelligence (XAI) further strengthened the framework by improving transparency and interpretability. Healthcare professionals reported high levels of trust and usability in the system due to its ability to explain predictions through feature importance and decision reasoning. This is particularly important in healthcare environments where clinical accountability and decision justification are essential. Overall, the study highlights that combining predictive intelligence with explainability is crucial for real-world adoption in sensitive healthcare domains.

Conclusion

The study concludes that an AI-integrated pharmacovigilance and climate-sensitive disease surveillance framework provides an effective and reliable solution for improving pediatric healthcare outcomes in urban Pakistan. The system successfully integrates multiple data sources to enable real-time detection of adverse drug reactions and climate-related disease outbreaks. The results demonstrate that AI-based predictive models significantly enhance surveillance accuracy compared to traditional approaches.

Moreover, the incorporation of Explainable AI ensures that the system is not only accurate but also transparent and trustworthy. This dual capability of prediction and explanation makes the framework highly suitable for deployment in healthcare environments where decision-making requires both precision and interpretability. The study therefore concludes that AI-driven integrated surveillance systems represent a necessary advancement for strengthening public health infrastructure in climate-vulnerable and resource-constrained settings.

Implications of the Study

The theoretical implication of this study lies in its contribution to the integration of pharmacovigilance, climate-sensitive epidemiology, and Explainable Artificial Intelligence into a unified surveillance framework. It expands the existing body of knowledge by demonstrating that healthcare prediction systems must incorporate environmental, pharmaceutical, and clinical dimensions simultaneously to achieve higher accuracy and relevance.

From a practical perspective, the study provides a scalable model that can be implemented in hospitals, public health departments, and national surveillance systems. It enables early detection of disease outbreaks and adverse drug reactions, thereby reducing healthcare burden, improving patient safety, and enhancing clinical decision-making. The framework also supports data-driven healthcare planning and resource allocation in urban settings.

At the policy level, the findings emphasize the need for integrating AI-based surveillance systems into national health strategies. Policymakers can utilize these insights to strengthen digital health infrastructure, improve drug safety monitoring systems, and develop climate-resilient healthcare policies. This is particularly important for Pakistan, where urbanization and climate change are intensifying public health challenges.

Future Directions

Future research should focus on deploying the proposed framework in real-time hospital environments to evaluate its operational performance under live conditions. Integration with Internet of Things (IoT)-based health monitoring devices and wearable technologies could further enhance real-time data collection and predictive accuracy.

Additionally, future studies may incorporate advanced deep learning architectures such as transformer models and graph neural networks to improve the detection of complex and multi-dimensional health patterns. Expanding the system to include rural healthcare settings would

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ISSN: (e) 3007-1607 (p) 3007-1593

also improve generalizability and national-level applicability.

Another important direction is the development of fully automated decision-support systems that not only predict risks but also recommend clinical interventions. Enhancing the explainability component with more user-friendly visualization tools for non-technical healthcare workers is also recommended.

Recommendations

It is recommended that healthcare institutions in Pakistan adopt AI-integrated surveillance systems to improve early detection of pediatric health risks. Training programs should be conducted for healthcare professionals to enhance their understanding of AI-driven decision-support tools and improve system utilization.

Government health agencies should invest in developing integrated data infrastructure that combines pharmacovigilance, clinical records, and environmental monitoring systems. This will enable more effective implementation of predictive surveillance frameworks at a national level.

It is also recommended that Explainable AI techniques be made a mandatory component of healthcare AI systems to ensure transparency, trust, and ethical use of predictive models. Collaboration between healthcare providers, data scientists, and policymakers should be strengthened to ensure successful deployment.

Limitations of the Study

Despite its contributions, the study has several limitations. First, the model was evaluated using a combination of historical datasets and simulated environmental data, which may not fully capture real-world complexities and unexpected variations in healthcare environments.

Second, the expert evaluation was limited to a relatively small sample of healthcare professionals, which may restrict the generalizability of qualitative findings across all healthcare settings in Pakistan.

Third, while the model incorporates multiple data sources, the availability and quality of pharmacovigilance and environmental data in developing contexts remain inconsistent, which may affect long-term scalability.

Finally, although explainability techniques were applied, the interpretation of AI outputs still requires a certain level of technical expertise, which may limit usability among non-technical healthcare staff. Future improvements should focus on simplifying interpretability and enhancing user accessibility.

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