International Journal of Medical and All Body Health Research

AI-Based Risk Modeling of Infectious Disease Spread and Its Implications for Public Health Security in Vulnerable Populations

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Article Info

ISSN (online): 2582-8940
Volume: 05
Issue: 04
October-December 2024
Received: 29-10-2024
Accepted: 31-11-2024
Page No: 241-250

Abstract

One of the challenges vulnerable populations in low-resource and high-density settings face includes the high probability of encountering an infectious disease outbreak because of the inadequate healthcare, overcrowding, and limited access to preventive services in such regions. Most traditional analytics in epidemiology do not address the challenges of modeling disease in these regions and thus fail to analyze the gaps in intervention and public health preparedness. This study focuses on the use of artificial intelligence (AI) based risk modeling systems to address infectious disease spread and public health security among these vulnerable populations. From epidemiology to public health, the response is built on machine learning (supervised, unsupervised, deep learning) algorithms on diverse datasets. These datasets include epidemiological incidences, population density, human mobility, health system, and socioeconomic and environmental factors. The identification of the disease's transmission location, prediction of the disease, and vulnerability of the health system to the disease model the outbreaks, serving the gaps in public health preparedness. These benefits of AI-based risk modeling assist the decision-making in the optimal allocation of resources such as hospital capacity, the availability of rapid diagnostic tests, and the focus of vaccination.

DOI: https://doi.org/10.54660/IJMBHR.2024.5.4.241-250

Keywords: Artificial Intelligence, Infectious Disease Transmission, Risk Modeling, Vulnerable Populations

Introduction

Vulnerable populations particularly those residing in high-density and low-resource environments infectious diseases remain a leading cause of morbidity and mortality, posing persistent challenges to epidemiology and public health security (Aik *et al*., 2020; Moodley *et al*., 2021). Urban slums, informal settlements, refugee camps, and remote rural communities are disproportionately affected by overcrowding, inadequate sanitation, fragile healthcare infrastructure, and limited access to preventive services such as immunization and health education. These structural and socioeconomic conditions interact with high population density to accelerate infectious disease transmission, intensifying outbreak impacts on individuals, households, and already strained health systems (Baker *et al*., 2022; Semenza *et al*., 2022). Recent epidemics including COVID-19, cholera, and Ebola virus disease have exposed critical gaps in global health equity and preparedness, underscoring how vulnerable populations experience faster disease spread, delayed detection, and suboptimal response outcomes (Nnaji *et al*., 2021; Kohnert, 2021).

Within these contexts, disease surveillance, risk modeling, and control are constrained by substantial structural and operational challenges. Traditional epidemiological systems rely heavily on manual case reporting, episodic data collection, and centralized laboratory confirmation, resulting in delayed outbreak detection and limited situational awareness (Ibrahim, 2020; Leitmeyer *et al*., 2020). These limitations are exacerbated by underreporting, weak diagnostic capacity, and fragmented health information systems, which restrict the generation of timely, accurate, and spatially resolved insights into infectious disease transmission dynamics. Furthermore, high population mobility, informal settlement layouts, and fluid social networks complicate contact tracing and transmission pathway analysis (Chisholm *et al*., 2020; Nadimpalli *et al*., 2020). Collectively, these constraints undermine the ability of public health authorities to anticipate outbreaks, prioritize high-risk populations, allocate resources efficiently, and implement targeted interventions, thereby heightening public health security risks.

In response to these challenges, artificial intelligence (AI) has emerged as a powerful enabler of predictive analytics and advanced risk modeling in epidemiology. Machine learning and deep learning approaches can process large volumes of heterogeneous data including epidemiological case reports, human mobility patterns, environmental indicators, and health system capacity metrics—to generate real-time estimates of disease transmission and outbreak trajectories (Luca *et al*., 2021; Rahman *et al*., 2021). AI-driven models support the early identification of transmission hotspots, assessment of population-level vulnerability, and optimization of intervention strategies under conditions of uncertainty. By integrating traditional surveillance data with non-traditional sources such as social media signals, satellite imagery, and mobile phone derived mobility data, AI enhances situational awareness and enables proactive, evidence-based decision-making for infectious disease control and public health security (Agbehadji *et al*., 2020; Zeng *et al*., 2021).

The persistence and disproportionate burden of infectious diseases among vulnerable populations can be theoretically explained through Social Determinants of Health Theory and Ecosocial Theory of Disease Distribution. Social Determinants of Health Theory posits that health outcomes are shaped by socioeconomic conditions such as income, housing quality, access to healthcare, education, and environmental exposure rather than biomedical factors alone. In high-density, low-resource settings, structural disadvantages like overcrowding, inadequate sanitation, informal employment, and weak health systems create conditions that amplify infectious disease transmission and limit effective prevention and response.

Ecosocial Theory further extends this understanding by emphasizing how social, political, and ecological contexts become biologically embodied over time, influencing population-level susceptibility to disease. Vulnerable populations experience repeated exposure to pathogenic environments, environmental degradation, and chronic stressors that increase disease susceptibility and accelerate transmission dynamics. These theoretical perspectives explain why outbreaks such as COVID-19, Ebola, and cholera disproportionately affect marginalized communities and why conventional surveillance systems struggle to capture these complex, multi-layered risks in real time.

From a systems perspective, Complex Adaptive Systems Theory provides a critical lens for understanding infectious disease spread in vulnerable populations. Infectious disease transmission emerges from non-linear interactions among individuals, mobility patterns, environmental conditions, and healthcare capacity. Traditional epidemiological models, which assume static relationships and homogeneous populations, are poorly equipped to capture such complexity. This theoretical limitation underscores the need for adaptive, data-driven approaches such as AI-based risk modeling that can dynamically learn from evolving system behaviors and feedback loops.

The limitations of traditional epidemiological surveillance in vulnerable settings can be conceptualized using Information Asymmetry Theory and Surveillance Theory. Information Asymmetry Theory explains how decision-makers operate with incomplete or delayed information due to fragmented reporting systems, under-detection, and informal healthcare-seeking behaviors common in low-resource environments. This asymmetry leads to delayed interventions, inefficient resource allocation, and reactive rather than preventive responses.

Surveillance Theory further highlights how conventional public health surveillance relies on institutional reporting structures that often exclude informal settlements, undocumented populations, and community-level health events. As a result, disease intelligence systems systematically underrepresent vulnerable populations, creating blind spots in outbreak detection and risk assessment. These structural weaknesses reduce the effectiveness of disease control strategies and undermine public health security by allowing outbreaks to escalate unnoticed.

The problem is compounded by Risk Society Theory, which posits that modern societies increasingly face systemic, transboundary risks such as pandemics that cannot be managed through traditional governance mechanisms alone. In the context of infectious diseases, risk is no longer localized or linear but rapidly propagates across social, economic, and geographic boundaries. Traditional epidemiological tools lack the predictive agility required to manage these evolving risks, particularly in populations where data scarcity and infrastructural fragility prevail.

Despite growing interest in AI for epidemiology, a clear theoretical and empirical gap remains. Technology Diffusion Theory suggests that innovations often fail to reach populations with the greatest need due to infrastructural, institutional, and capacity constraints. Most AI-based infectious disease models have been developed and validated using data from high-income or well-instrumented settings, limiting their applicability to vulnerable populations characterized by data sparsity, informal mobility, and weak surveillance systems.

Additionally, Equity Theory highlights that technological interventions may inadvertently reinforce existing disparities if vulnerable populations are underrepresented in training datasets or excluded from system design. Many AI models prioritize prediction accuracy over equity, fairness, and contextual relevance, resulting in biased risk estimates that fail to capture the true burden of disease in marginalized communities.

From a methodological standpoint, existing studies often focus on technical performance metrics (e.g., accuracy, precision) without adequately linking model outputs to public health security outcomes, such as early warning capacity, surge preparedness, or equitable resource allocation. This creates a gap between AI innovation and actionable public health decision-making. Your study directly addresses this gap by centering vulnerable populations, integrating diverse risk determinants, and framing AI-based modeling as a public health security tool rather than a purely computational exercise.

Methodology

This study employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to systematically evaluate literature on AI-based risk modeling of infectious disease spread and its implications for public health security, particularly in vulnerable populations. A comprehensive search strategy was developed to identify relevant studies from major electronic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, covering publications from 2010 to 2024. Keywords and controlled vocabulary included terms related to artificial intelligence, machine learning, infectious disease modeling, outbreak prediction, risk assessment, public health security, and vulnerable or high-risk populations. Only peer-reviewed articles, conference proceedings, and high-quality modeling studies published in English were included to ensure methodological rigor and relevance.

All retrieved records were imported into reference management software, and duplicate entries were removed. Initial screening of titles and abstracts was performed independently by multiple reviewers based on predefined inclusion criteria, focusing on studies that applied AI methods to predict infectious disease dynamics, quantify outbreak risk, or assess impacts on populations with heightened vulnerability due to socioeconomic, demographic, or health-related factors. Studies were excluded if they were purely theoretical without empirical validation, unrelated to disease modeling, or focused solely on clinical diagnosis without population-level risk assessment. Full-text screening followed, with reasons for exclusion documented to maintain transparency and reproducibility.

Data extraction utilized a standardized template to capture study characteristics, AI methodologies employed, input data sources, modeling frameworks, population context, validation methods, key findings, and implications for public health policy and intervention strategies. Quality assessment and risk of bias were conducted using adapted appraisal tools appropriate for computational, observational, and simulation-based studies, emphasizing data representativeness, model robustness, predictive accuracy, and applicability to vulnerable populations. Due to heterogeneity in modeling approaches, data sources, and outcome measures, a narrative synthesis was performed rather than a quantitative meta-analysis. This synthesis systematically compared AI techniques, risk assessment outputs, and public health implications, highlighting strengths, limitations, and research gaps.

The data integration and modeling strategy in this study is grounded in Systems Theory and Data Fusion Theory. Systems Theory supports the integration of epidemiological, demographic, environmental, mobility, and health system indicators, recognizing infectious disease spread as the outcome of interacting subsystems rather than isolated variables. AI-based models operationalize this theory by learning non-linear relationships across heterogeneous datasets, allowing for holistic risk assessment.

Data Fusion Theory further justifies the combination of structured data (case counts, hospital capacity) with unstructured or semi-structured data (mobility data, social signals, environmental indicators). By synthesizing multi-source inputs, AI models reduce uncertainty, compensate for missing data, and improve predictive robustness—particularly critical in settings with underreporting and delayed diagnostics.

The application of supervised, unsupervised, and deep learning techniques aligns with Predictive Analytics Theory, which emphasizes forecasting future states based on historical and real-time data patterns. Supervised learning supports probabilistic risk classification, unsupervised learning enables anomaly detection and hotspot identification, and deep learning captures spatiotemporal dynamics consistent with Network Theory, where transmission occurs through interconnected social and mobility networks.

Also, the emphasis on validation, uncertainty quantification, and scenario analysis reflects Decision Theory, ensuring that model outputs are interpretable, actionable, and suitable for policy use. This theoretical grounding ensures that AI-based risk modeling is not merely descriptive but directly supports evidence-based decision-making, equitable intervention planning, and strengthened public health security

In order to support public health decision-making, the conceptual framework for AI-based risk modeling of infectious disease propagation in susceptible populations is based on the integration of sophisticated computational algorithms with a variety of epidemiological, demographic, and environmental data. In order to forecast the dynamics of disease transmission, identify high-risk locations, and evaluate the vulnerabilities of the health system, this framework places artificial intelligence (AI) and machine learning (ML) as key analytical tools. The framework offers an organized method for enhancing public health security in high-density and low-resource environments by fusing multi-source data with predictive modeling (Oparah *et al*., 2022; Liu *et al*., 2022).

When used to risk modeling, AI and machine learning techniques cover a broad range of methods intended to identify trends, categorize risk levels, and predict outbreak trajectories. Logistic regression, decision trees, random forests, and gradient boosting algorithms are examples of supervised learning techniques that are frequently used to forecast disease occurrence, categorize populations or regions according to risk level, and calculate outbreak probabilities using past epidemiological data. Unexpected patterns, new hotspots, or departures from baseline transmission trends can be found using unsupervised learning techniques including clustering, dimensionality reduction, and anomaly detection. While hybrid models that combine mechanistic epidemiological models with AI improve predictive accuracy by fusing theoretical knowledge of transmission processes with data-driven insights, deep learning architectures such as recurrent neural networks and long short-term memory models are especially good at capturing spatiotemporal patterns in disease dynamics.

Integrating diverse data sources is a fundamental aspect of the architecture. Confirmed cases, laboratory test findings, and syndromic surveillance indicators are examples of epidemiological data that offer precise measurements of disease burden and epidemic status. The vulnerability and possible exposure of susceptible communities are informed by demographic data, such as population density, age distribution, household composition, and social contact networks. Temperature, precipitation, humidity, land use, and sanitary infrastructure are examples of environmental and climatic indicators that capture ecological and contextual elements that affect pathogen survival, vector dynamics, and transmission risk. AI models can produce complex, context-specific risk evaluations that take into account both biological and social factors of disease spread by integrating these data streams (Ikhalea *et al*., 2022; Chianumba *et al*., 2022).

It is necessary to pay attention to certain structural and behavioral aspects that increase risk in order to comprehend the dynamics of disease transmission in vulnerable groups. Rapid illness spread and delayed discovery are caused by a number of factors, including high population density, poor housing, restricted access to healthcare, and mobility patterns. By simulating the effects of these variables, AI-based risk models can pinpoint possible routes of transmission, groups of people or communities at high risk, and intervention sites. These models also make scenario analysis easier, allowing public health officials to assess how well focused treatments, resource allocation plans, and preventive measures work in various outbreak scenarios.

The conceptual framework establishes a direct connection between public health security goals and AI-based risk modeling. AI models facilitate proactive planning, quick reaction, and strategic resource deployment by offering early warning of possible outbreaks, identifying high-risk locations for intervention, and evaluating vulnerabilities in healthcare infrastructure. Predictive insights are guaranteed to influence operational decision-making, biosecurity protocols, and emergency preparedness through integration with national and regional health security policies (Bardosh *et al*., 2020; Bedi *et al*., 2021). All things considered, this approach highlights the strategic importance of AI-driven risk modeling in improving situational awareness, reducing the spread of disease, and bolstering the ability of vulnerable people and health systems to withstand threats from infectious diseases.

Data Sources and Indicators

The development and use of artificial intelligence (AI) in infectious disease risk modeling depend heavily on accurate and thorough data. Multidimensional datasets are used by AI-driven methods to forecast outbreak trajectories, characterize disease dynamics, and guide focused public health actions. While guaranteeing data quality, completeness, and timeliness, effective modeling incorporates epidemiological, demographic, health system, environmental, and socioeconomic indicators.

The primary inputs for AI-based illness modeling include laboratory confirmations, syndromic surveillance, and epidemiological case data. Direct proof of disease occurrence and temporal trends is provided by case data, which includes reported incidences of infection, hospitalizations, and mortality. Syndromic surveillance provides early warning signs of potential outbreaks by capturing patterns of symptom presentation, frequently prior to formal diagnoses being established. By confirming suspected infections and allowing stratification by pathogen type, strain, or resistance profile, laboratory-confirmed cases significantly improve model accuracy. These diverse sources can be assimilated by AI algorithms, especially machine learning models, to detect aberrant illness patterns, predict case counts, and calculate the likelihood of transmission under various circumstances (Reddy *et al*., 2021; Hamilton *et al*., 2021).

AI risk models are progressively including social contact networks, population density, and migration patterns all of which are important factors in the spread of disease. Rapid transmission is facilitated by high-density urban environments, and the spatial dissemination of infectious agents is influenced by population movements such as daily commuting, migration, and travel. Proxy indicators of human movement and contact patterns include social media interactions, mobile phone data, and travel logs. These data can be used by network-based modeling techniques to identify super-spreader nodes, simulate transmission paths, and analyze the possible effects of intervention strategies like targeted vaccination or social distancing. The predictive realism of AI-driven epidemic simulations is improved by incorporating such spatial and behavioral dynamics.

For evaluating public health resilience and simulating the possible effects of epidemics on healthcare delivery, health system capacity indicators are crucial. Models of healthcare burden and system stress during epidemics are informed by metrics including hospital bed availability, intensive care unit (ICU) capacity, ventilator supply, and personnel levels. These indications can be incorporated into AI-based simulations to forecast resource shortages, optimize distribution, and facilitate scenario-based surge capacity planning. Incorporating health system factors guarantees that risk evaluations are not only epidemiological but also operationally relevant, directing emergency response planning and policy decisions (Anderson *et al*., 2020; Decouttere *et al*., 2021).

Disease susceptibility and spread are greatly influenced by socioeconomic and environmental factors. While urbanization, sanitation, and housing conditions alter exposure risk, climate variables including temperature, humidity, and rainfall impact pathogen viability and vector dynamics. Both vulnerability and the efficacy of therapies are influenced by socioeconomic factors, such as income levels, educational attainment, and access to healthcare. In order to identify high-risk communities and prioritize interventions based on environmental and social determinants of health, AI models can integrate geographic and contextual datasets to capture these intricate interconnections.

Important issues in AI-based risk modeling continue to include data timeliness, completeness, and quality. Bias can be introduced, model accuracy can be decreased, and actionable insights can be limited by incomplete case reporting, delayed laboratory confirmations, irregular coding standards, and missing demographic data. Data harmonization, imputation techniques for missing values, validation against several sources, and the usage of real-time or almost real-time reporting systems are some strategies to lessen these problems. The reliability and repeatability of modeling results are further improved by transparent documentation of data provenance and quality evaluations.

The integration of a variety of high-quality datasets, including epidemiological, demographic, health system, environmental, and socioeconomic indicators, is essential for AI-driven infectious disease risk modeling. Early epidemic detection, accurate transmission dynamics prediction, and evidence-based public health decision-making are all made possible by the efficient use of this data. For trustworthy modeling and the development of interventions that protect vulnerable populations and improve overall public health security, it is crucial to ensure data completeness, accuracy, and timeliness while capturing the multifactorial determinants of disease spread (Tang *et al*., 2020; Sartorius *et al*., 2021).

AI-Based Predictive Modeling Techniques

Predictive modeling techniques based on artificial intelligence (AI) have emerged as crucial tools for comprehending, predicting, and reducing the transmission of infectious diseases, especially in vulnerable populations with limited healthcare resources. These methods evaluate heterogeneous data streams, find patterns, predict outbreak trajectories, and guide public health responses by utilizing machine learning (ML) and deep learning algorithms. AI-driven models offer a more proactive and accurate approach to disease surveillance than conventional epidemiological approaches by converting vast amounts of epidemiological, demographic, mobility, and environmental data into actionable insights (Chianumba *et al*., 2021; Chakilam, 2022).

One of the most popular AI methods for risk assessment and epidemic forecasting is supervised learning. In supervised learning, predictive variables like population density, movement patterns, and environmental conditions are matched with known outcomes like verified disease cases or epidemic occurrences in labeled datasets. The probability of infection or outbreak breakout can then be used to categorize areas, communities, or individuals using algorithms like logistic regression, decision trees, random forests, support vector machines, and gradient boosting models. By identifying high-risk locations early on, these models help public health authorities prioritize resource allocation, carry out focused interventions, and predict healthcare demand. Additionally, as fresh data becomes available, supervised learning enables ongoing model performance enhancement, increasing the accuracy of outbreak prediction over time.

Unsupervised learning methods are especially helpful for identifying clusters and detecting anomalies. Unlike supervised approaches, unsupervised models find inherent patterns or structures in the data rather than depending on labeled outcome data. In high-density populations, clustering techniques like k-means, hierarchical clustering, and density-based spatial clustering might identify emergent outbreak clusters or hitherto unknown hotspots of disease transmission. According to Karadayi *et al*. (2020) and Mehrdad *et al*. (2021), anomaly detection techniques can detect anomalous deviations from predicted epidemiological trends, indicating possible outbreaks or emergent dangers that may not yet have been reported. In situations like low-resource health systems or informal settlements where formal reporting is inconsistent, partial, or delayed, these qualities are essential for early warning.

Deep learning expands AI models' predictive power to include intricate network-based and spatiotemporal studies. For capturing temporal trends, spatial dependencies, and non-linear interactions in epidemiology and mobility data, recurrent neural networks (RNNs), long short-term memory (LSTM) models, and convolutional neural networks (CNNs) are especially well-suited. These models may simulate the effects of interventions, predict disease trajectories over time and geography, and pinpoint important nodes in transmission networks, such as highly connected people or busy areas. Deep learning algorithms enable proactive decision-making in high-risk urban and rural environments by providing high-resolution forecasts of outbreak dynamics through the use of multi-dimensional inputs.

Hybrid models improve predicted accuracy and interpretability by fusing AI with mechanistic epidemiology techniques. Theoretical knowledge of disease transmission processes and population interactions is included into mechanistic models, such as the susceptible-infected-recovered (SIR) or susceptible-exposed-infected-recovered (SEIR) frameworks. Data-driven parameter estimate, dynamic modification to real-time inputs, and enhanced adaptability to changing situations are all made possible by integrating these models with AI algorithms. By utilizing AI's analytical capabilities to manage massive, diverse information, hybrid models can close the gap between theoretical epidemiology and empirical data and produce forecasts that are easy to understand.

Strict model validation, calibration, and uncertainty quantification are necessary for the successful application of AI-based prediction models. In order to evaluate accuracy and generalizability, validation entails testing model predictions against independent datasets or observed outbreak results. Model parameters, such as population demographics, healthcare capacity, and migration patterns, are calibrated to represent local epidemiological conditions. For policymakers and public health professionals to understand the accuracy and limitations of forecasts, uncertainty quantification which includes confidence intervals, sensitivity assessments, and probabilistic forecasting is crucial (Faes and Moens, 2020; Murad *et al*., 2021). By taking care of these issues, AI models are guaranteed to be not only technically sound but also practical and morally upright.

Deep learning, supervised and unsupervised learning, and hybrid mechanistic-AI models are examples of AI-based predictive modeling techniques that offer strong instruments for predicting infectious disease outbreaks, evaluating risk, and guiding public health actions. These methods improve early warning capacities, maximize resource allocation, and strengthen the resilience of vulnerable populations and health systems in the face of changing infectious disease threats when paired with thorough validation and uncertainty assessment.

Applications in Vulnerable Populations

Infectious disease risk modeling based on artificial intelligence (AI) has shown great promise for improving public health security, especially for vulnerable groups. During infectious disease epidemics, vulnerable populations typically characterized by socioeconomic deprivation, limited access to healthcare, high population density, or underlying health conditions face disproportionate risks (Shi and Stevens, 2021; Siegel and Mallow, 2021). By using AI in these situations, health inequities can be decreased and resilience can be increased in both urban and resource-constrained settings through more accurate risk area detection, anticipatory planning, and customized intervention tactics.

One fundamental use of AI-driven modeling is risk mapping in informal communities and high-density urban settlements. Inadequate sanitation, a lack of healthcare facilities, and excessive mobility are common characteristics of slums, densely populated urban districts, and informal settlements, all of which promote the quick spread of infectious diseases. In order to create comprehensive risk maps, AI algorithms in particular, spatial machine learning and geographic prediction models can incorporate epidemiology data, population density measures, mobility patterns, and environmental elements. These maps help authorities prioritize surveillance and intervention activities by identifying communities or neighborhoods that are more vulnerable to the spread of diseases. AI techniques offer actionable insights that go beyond conventional aggregate-level epidemiological reporting by showing risk gradients at a fine-grained spatial level.

Another crucial application in vulnerable populations is the use of predictive analytics for surge planning and the distribution of healthcare resources. High-risk community outbreaks frequently put a strain on the local healthcare system, resulting in a shortage of hospital beds, intensive care units (ICUs), medical staff, and necessary supplies. AI-based models that take into account disease transmission rates, population demographics, comorbidities, and healthcare consumption trends can predict the demand for healthcare resources under various epidemic scenarios. Decision-makers can use these prediction outputs to create temporary care facilities, deploy mobile clinics, and allocate resources as efficiently as possible. AI helps lower morbidity and death in populations with low baseline healthcare capability by facilitating proactive rather than reactive planning (Paramasivan, 2020; Chianumba *et al*., 2021).

Another crucial use of AI is the identification of hotspots for focused interventions and immunization programs. Spatially diverse risk profiles, where transmission is concentrated in particular towns, marketplaces, schools, or transportation centers, may be experienced by vulnerable people. To identify new hotspots, AI systems can examine environmental factors, transportation networks, and epidemiological patterns. With the use of these data, public health officials are able to put specific policies into place, such as vaccination campaigns that are given priority, increased community involvement, and localized non-pharmaceutical interventions like temporary travel restrictions or cleanliness promotion. Targeted strategies increase productivity, minimize resource waste, and optimize protective effects on the most vulnerable populations.

Another important advantage of AI-driven monitoring is its ability to support biosecurity and containment tactics in environments with limited resources. Numerous vulnerable people live in areas with inadequate emergency response infrastructure, unreliable disease reporting, or limited laboratory capability. By including alternative data sources, such as syndromic surveillance, mobile phone mobility data, environmental monitoring, and community-reported health signals, AI-based models can make up for these constraints. AI makes it possible to detect epidemics in a timely manner, promotes coordinated containment actions, and, when practical, assists the development of quarantine or isolation tactics through predictive risk mapping and early warning systems. Crucially, these technologies promote community resilience to infectious disease threats by improving situational awareness even in areas with limited resources (Kakkar *et al*., 2020).

Risk mapping, predictive resource planning, hotspot identification, and biosecurity support are examples of AI applications in vulnerable populations that collectively improve the ability to anticipate, mitigate, and respond to infectious disease risks. AI makes it possible to precisely target interventions, allocate limited healthcare resources effectively, and implement proactive containment methods by combining spatial, epidemiological, and socioeconomic data. These skills are especially important in low-resource environments, informal groups, and high-density urban areas where conventional public health methods might not be enough. Through these applications, AI-driven risk modeling advances national and international health security by strengthening protection of vulnerable populations, improving outbreak preparedness and response, and promoting equitable public health outcomes (Zahid and Shankar, 2020; Ejedegba, 2022).

Implications for Public Health Security

AI-based risk modeling of infectious disease transmission has significant implications for public health security, especially when it comes to safeguarding vulnerable groups in high-density, low-resource environments. The ability of a country to prevent, identify, and successfully address biological threats whether they are intentional, unintentional, or naturally occurring is referred to as public health security (O'Sullivan and Ramsay, 2020; Lentzos *et al*., 2020). Predictive AI model adoption improves health systems' strategic ability to foresee outbreaks, distribute resources effectively, and carry out prompt interventions, ultimately reducing socioeconomic and health effects.

Early warning and proactive reaction capabilities are two important contributions of AI-based models. Conventional surveillance methods frequently depend on delayed reporting, which makes it more difficult for health officials to take action before the spread of disease worsens. AI models, on the other hand, are capable of real-time analysis of multi-source data, such as demographic indicators, migration patterns, environmental elements, and epidemiological case reports, in order to spot anomalous trends or departures from typical patterns. Early detection of possible outbreaks is made possible by this capability, which enables quick reaction team mobilization, medical supply prepositioning, and containment measures to be put in place before widespread transmission takes place (Martins *et al*., 2020; Chen *et al*., 2022). Early warning reduces morbidity, mortality, and disruption to health systems and society by enabling proactive rather than reactive responses.

Prioritizing treatments to safeguard high-risk populations is also supported by AI-driven risk modeling. Predictive models direct the targeted distribution of resources like vaccines, diagnostic tests, and treatments by identifying geographic hotspots, demographic groups, or particular areas at elevated risk. Interventions can be concentrated in regions with the highest risk of transmission in high-density urban settlements or informal groups, increasing the effectiveness and equality of public health initiatives. In a similar vein, models can guide non-pharmaceutical interventions like movement restrictions, quarantines, or health education campaigns, guaranteeing that high-risk populations receive prompt protection while reducing needless disturbance in lower-risk areas (Imai *et al*., 2020; Regmi and Lwin, 2021).

Preparation and reaction are further strengthened by integrating AI-based surveillance with emergency planning and national health security frameworks. To improve situational awareness and coordination, predictive insights can be integrated into current decision-making procedures, emergency operation centers, and health information systems. Public health authorities may guarantee a unified, multi-sectoral response to new dangers by connecting AI outputs to strategic resource allocation, hospital surge planning, and interagency communication. Policymakers can assess possible actions under various epidemic scenarios and optimize response methods in line with national security goals thanks to AI models' help for scenario simulations and contingency planning.

Beyond domestic uses, AI-based risk modeling makes a substantial contribution to pandemic preparedness and global health security. Outbreaks in susceptible populations can swiftly spread to other areas or nations because infectious illnesses do not respect national boundaries. International cooperation, surveillance, and coordinated containment strategies are informed by early insights into possible cross-border spread provided by AI models that integrate mobility and environmental data. AI helps international health authorities, including the World Health Organization, prioritize resources, send out early alarms, and direct initiatives in areas at risk by improving predictive power.Additionally, AI-based models' scalability and adaptability enable the quick integration of new pathogens or emerging epidemiological trends, strengthening the global health infrastructure's ability to effectively respond to pandemics in the future (Abir *et al*., 2020; Nguyen *et al*., 2021).

By facilitating early warning, focused interventions, integration with emergency planning, and contributions to global preparedness, AI-based predictive modeling greatly enhances public health security. AI improves health systems' capacity to safeguard vulnerable populations, maximize resources, and preserve social stability in the face of infectious disease risks by offering timely, data-driven insights into disease dynamics (Majeed and Hwang, 2021; Chianumba *et al*., 2021). Its adoption strengthens national and international capacities for outbreak prevention, mitigation, and resilient response, marking a significant advancement in contemporary epidemiology.

Challenges and Limitations

Although AI-driven infectious disease risk modeling has the potential to revolutionize public health, its application is fraught with difficulties and constraints, especially when it comes to vulnerable groups. To guarantee dependable, fair, and useful results, these limitations which span the technical, operational, ethical, and sociopolitical domains must be addressed. Designing reliable surveillance systems and appropriately interpreting model outputs require an understanding of these constraints.

Data shortages, reporting delays, and under-detection in vulnerable communities are some of the main issues. The lack of access to healthcare and disease surveillance facilities in rural areas, informal settlements, and marginalized groups sometimes leads to inconsistent or inadequate epidemiological data. Underestimating the incidence of disease might result from inconsistent syndromic surveillance, delayed laboratory confirmation, and fragmented case reporting. According to Bates *et al*. (2020) and Prosperi *et al*. (2020), AI models trained on such insufficient datasets may provide skewed risk projections, decreasing their predictive reliability and perhaps misguiding interventions. Furthermore, real-time modeling which is essential for early epidemic identification and prompt resource allocation is hampered by delayed data entry and asynchronous reporting. Addressing these gaps requires investment in data infrastructure, standardization of reporting protocols, and incorporation of alternative data streams such as mobile health reporting, environmental monitoring, and community-based surveillance.

AI applications for public health are further constrained by representativeness and algorithmic bias. To identify disease trends and forecast the dynamics of transmission, machine learning models use both historical and modern datasets. The health dynamics of well-represented communities may be disproportionately reflected in model outputs if specific populations or geographic areas are overrepresented while vulnerable groups are underrepresented. By misallocating resources and underestimating risk in underrepresented populations, this can worsen health inequities. Algorithmic decisions that unintentionally favor some results over others, such as feature selection, covariate weighting, and model architecture, can also result in bias (Chakraborty *et al*., 2021; Mehrabi *et al*., 2021). Continuous evaluation of model fairness, incorporation of diverse and representative datasets, and application of bias mitigation techniques are therefore critical to ensure equity in AI-driven public health interventions.

The practical usefulness of AI-based risk modeling is further limited by resource limitations for model implementation and interpretation. Strong IT infrastructure, specialized knowledge, and substantial processing power are frequently needed for high-performance AI models. The deployment and upkeep of AI systems may be hampered by low-resource health systems' inability to utilize these capabilities. Additionally, competent staff who can convert probabilistic forecasts into practical public health decisions are needed to comprehend complex model results. Models run the risk of being misused, misunderstood, or abandoned in the absence of sufficient technological and human resources, compromising their intended influence on public health. To close this gap and enable the long-term incorporation of AI technologies into standard surveillance workflows, capacity building, training initiatives, and user-friendly platforms are crucial (Hungbo *et al*., 2020; Forkuo *et al*., 2022).

One major issue in data collection and modeling is ethical and privacy considerations. For AI models to produce precise forecasts, they frequently need access to private health, mobility, and demographic data. Data misuse, confidentiality violations, and unintentional re-identification can have major social and legal repercussions among vulnerable populations. System design must take ethical factors into account, such as informed permission, data minimization, purpose limitation, and equitable benefit distribution (Pratt *et al*., 2020; Reed-Berendt *et al*., 2022). If these issues are not resolved, community involvement in surveillance activities may decline, trust in public health authorities may be damaged, and the availability of high-quality data may be restricted, all of which might further undermine the efficacy of the model. Deploying AI in an ethical manner requires transparent governance structures, privacy-preserving computational methods, and community involvement.

Data scarcity and under-detection in susceptible populations, algorithmic bias, resource limitations, and ethical and privacy concerns are just a few of the many obstacles that AI-based infectious disease risk modeling must overcome. These restrictions have an impact on model accuracy, equity, and practical applicability, underscoring the necessity of meticulous system design, representative and superior data collecting, capacity building, and strong governance frameworks. In order to ensure that AI technologies not only improve epidemic preparedness and predictive skills but also contribute to fair and morally responsible public health outcomes, especially for communities most at risk, it is imperative that these concerns be addressed.

Future Directions and Research Opportunities

Predictive modeling based on artificial intelligence has already shown significant promise in supporting public health security and infectious disease surveillance. The efficacy, equity, and sustainability of AI-driven techniques, however, can be further improved by a number of future avenues and research opportunities as the field develops (Yigitcanlar *et al*., 2021; Palomares *et al*., 2021). Enhancing model transparency, incorporating dynamic data streams, encouraging cross-sectoral cooperation, and bolstering the body of evidence for operational and policy adoption are the main goals of these directions.

Improving model interpretability and developing explainable AI (XAI) techniques are important areas for future research. Many AI and machine learning models, especially deep learning architectures, operate as "black boxes," making predictions without providing a clear explanation of the underlying principles. Adoption and implementation in operational contexts may be hampered by this lack of openness, which can erode confidence among public health professionals and legislators. The goal of XAI research is to produce understandable results that show which input characteristics influence predictions and how risk assessments are produced. Explainable models can support ethical accountability in high-stakes public health initiatives, enhance stakeholder confidence, and enable informed decision-making by making AI outputs more comprehensible (McDermid *et al*., 2021; Kokala, 2022). Improving interpretability is especially crucial for vulnerable populations, because interventions need to be reasonable, equal, and sensitive to local circumstances.

Using real-time mobility and environmental data for adaptive forecasting is another interesting approach. The responsiveness of predictive models is limited by the fact that traditional epidemiological datasets frequently lag behind the present state of disease transmission. Near-real-time insights on population movement, social interactions, and ecological circumstances that impact disease spread can be obtained by integrating dynamic data sources, such as anonymized mobile phone location data, transportation network usage, and satellite-based environmental indicators. Emergent transmission hotspots may be identified, outbreak escalation can be predicted, and appropriate actions can be informed by adaptive forecasting models that continuously update predictions based on incoming data. Research is required to assure resilience across various geographic and socioeconomic situations, address privacy and ethical problems, and maximize the integration of these disparate data streams.

AI's cross-sectoral integration with social services, public health, and urban planning offers a calculated chance to enhance disease prevention in populations at risk. In addition to biological considerations, social determinants including housing density, sanitation, healthcare access, and community mobility patterns all have an impact on the dynamics of infectious diseases. AI models that integrate data from social services, education, transportation, and urban planning can offer a more comprehensive understanding of risk, enabling authorities to create multifaceted treatments that address both structural and direct causes of illness. In order to improve overall resilience and enable proactive, evidence-based interventions that are customized to local vulnerabilities, collaborative frameworks bridging public health, social policy, and urban management are necessary (Blanco *et al*., 2020; Ojeikere *et al*., 2021).

Lastly, research endeavors ought to prioritize policy acceptance, scalability, and empirical confirmation. To assess accuracy, generalizability, and reliability, predictive AI models need to be thoroughly evaluated against actual outbreak data. Diverse populations and geographical contexts should be included in validation studies to guarantee that models are resilient in high-density, low-resource, and other sensitive environments. Governments and public health organizations can confidently implement AI-supported decision-making by using the evidence from these studies to inform policy frameworks. Research on scalability, which focuses on computational efficiency, interoperability across health systems, and sustainable deployment techniques that enable models to function successfully at local, national, and international levels, is also crucial.

Increasing transparency, incorporating dynamic and cross-sectoral data, and developing a solid empirical basis for operational and policy adoption are the key to the future of AI-based infectious disease risk modeling. In an increasingly interconnected and complex world, research can improve public health systems' predictive capacity, equity, and resilience by addressing these priorities. This will ultimately support more proactive and successful interventions to protect vulnerable populations and strengthen global health security.

Conclusion

With its unparalleled capacity to forecast outbreak dynamics, evaluate population-level risk, and guide focused public health measures, AI-driven risk modeling has become a game-changing instrument in infectious disease monitoring. AI models offer complex, real-time insights into the transmission of disease by combining a variety of data sources, including mobility patterns, population density measures, environmental and socioeconomic variables, epidemiological case reports, and laboratory confirmations. In the end, these contributions improve the efficacy, promptness, and accuracy of public health actions by enabling early detection of nascent outbreaks, identifying high-risk communities, and optimizing the allocation of healthcare resources.

AI-driven risk modeling is especially strategically important for safeguarding vulnerable groups. Communities in resource-constrained environments, informal communities, and high-density urban settlements are disproportionately vulnerable to infectious disease risks and frequently lack a strong healthcare infrastructure. Health authorities can proactively target interventions like immunization campaigns, mobile clinics, and containment measures thanks to AI-enabled solutions that make risk mapping, hotspot detection, and predictive resource planning easier. AI modeling promotes fair resource distribution and increases resilience among those most vulnerable to unfavorable health outcomes by predicting the spread of disease and identifying populations at increased risk.

AI-driven risk modeling has important ramifications for national and international health security from a policy and practice standpoint. Predictive insights can help ensure that public health initiatives are evidence-based and focused at the national level by guiding emergency response operations, strengthening preparedness strategies, and strategically allocating healthcare resources. Globally, early warning systems are improved, coordinated international actions are supported, and the risk of transnational disease propagation is reduced by integration with cross-border surveillance networks and standardized data-sharing frameworks. In addition to investing in infrastructure and capacity building to support sustainable implementation, policymakers are urged to adopt governance frameworks that prioritize data protection, transparency, and ethical AI deployment.

By bridging predictive analytics, operational planning, and ethical governance, these approaches provide actionable intelligence that informs policy, improves preparedness, and fosters equitable and resilient public health systems at both national and international levels. AI-driven risk modeling is an important development in infectious disease surveillance, providing strategic tools to protect vulnerable populations and strengthen health security.

References

1. Abir SAA, Islam SN, Anwar A, Mahmood AN, Oo AMT. Building resilience against COVID-19 pandemic using artificial intelligence, machine learning, and IoT: a survey of recent progress. IoT. 2020;1(2):506-28. doi:10.3390/iot1020028.
2. Agbehadji IE, Awuzie BO, Ngowi AB, Millham RC. Review of big data analytics, artificial intelligence and nature-inspired computing models towards accurate detection of COVID-19 pandemic cases and contact tracing. Int J Environ Res Public Health. 2020;17(15):5330.
3. Aik J, Ong J, Ng LC. The effects of climate variability and seasonal influence on diarrhoeal disease in the tropical city-state of Singapore–A time-series analysis. Int J Hyg Environ Health. 2020;227:113517.
4. Anderson EL, Omenn GS, Turnham P. Improving health risk assessment as a basis for public health decisions in the 21st century. Risk Anal. 2020;40(S1):2272-99.
5. Baker RE, Mahmud AS, Miller IF, Rajeev M, Rasambainarivo F, Rice BL, *et al*. Infectious disease in an era of global change. Nat Rev Microbiol. 2022;20(4):193-205.
6. Bardosh KL, de Vries DH, Abramowitz S, Thorlie A, Cremers L, Kinsman J, *et al*. Integrating the social sciences in epidemic preparedness and response: a strategic framework to strengthen capacities and improve global health security. Global Health. 2020;16(1):120.
7. Bates DW, Auerbach A, Schulam P, Wright A, Saria S. Reporting and implementing interventions involving machine learning and artificial intelligence. Ann Intern Med. 2020;172(11 Suppl):S137-44.
8. Bedi JS, Vijay D, Dhaka P, Gill JPS, Barbuddhe SB. Emergency preparedness for public health threats, surveillance, modelling & forecasting. Indian J Med Res. 2021;153(3):287-98.
9. Blanco C, Wiley TR, Lloyd JJ, Lopez MF, Volkow ND. America’s opioid crisis: the need for an integrated public health approach. Transl Psychiatry. 2020;10(1):167.
10. Chakilam C. AI-Driven Insights In Disease Prediction And Prevention: The Role Of Cloud Computing In Scalable Healthcare Delivery. Migr Lett. 2022;19(S8):2105-23.
11. Chakraborty J, Majumder S, Menzies T. Bias in machine learning software: Why? how? what to do? In: Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering; 2021 Aug. p. 429-40.
12. Chen AP, Hansoti B, Hsu EB. The COVID-19 pandemic response and its impact on Post-Pandemic health emergency and disaster risk management in the united States. Sustainability. 2022;14(23):16301.
13. Chianumba EC, Ikhalea N, Mustapha AY, Forkuo AY. Developing a framework for using AI in personalized medicine to optimize treatment plans. J Front Multidiscip Res. 2022;3(1):57-71.
14. Chisholm RH, Crammond B, Wu Y, Bowen AC, Campbell PT, Tong SY, *et al*. A model of population dynamics with complex household structure and mobility: implications for transmission and control of communicable diseases. PeerJ. 2020;8:e10203.
15. Decouttere C, De Boeck K, Vandaele N. Advancing sustainable development goals through immunization: a literature review. Global Health. 2021;17(1):95.
16. Ejedegba EO. Equitable healthcare in the age of AI: predictive analytics for closing gaps in access and outcomes. Int J Res Publ Rev. 2022;3(12):2882-94.
17. Faes M, Moens D. Recent trends in the modeling and quantification of non-probabilistic uncertainty. Arch Comput Methods Eng. 2020;27(3):1-39.
18. Forkuo AY, Chianumba EC, Mustapha AY, Osamika D, Komi LS. Advances in digital diagnostics and virtual care platforms for primary healthcare delivery in West Africa. Methodology. 2022;96(71):48.
19. Hamilton AJ, Strauss AT, Martinez DA, Hinson JS, Levin S, Lin G, *et al*. Machine learning and artificial intelligence: applications in healthcare epidemiology. Antimicrob Steward Healthc Epidemiol. 2021;1(1):e28.
20. Hungbo AQ, Adeyemi CHR, Ajayi OO. Early warning escalation system for care aides in long-term patient monitoring. IRE Journals. 2020;3(7):321-45.
21. Ibrahim NK. Epidemiologic surveillance for controlling Covid-19 pandemic: types, challenges and implications. J Infect Public Health. 2020;13(11):1630-8.
22. Ikhalea N, Chianumba EC, Mustapha AY, Forkuo AY. A Conceptual Framework for AI-Driven Early Detection of Chronic Diseases Using Predictive Analytics. 2022. [Note: Journal/source details incomplete in original; formatted as available.]
23. Imai N, Gaythorpe KA, Abbott S, Bhatia S, van Elsland S, Prem K, *et al*. Adoption and impact of non-pharmaceutical interventions for COVID-19. Wellcome Open Res. 2020;5:59.
24. Kakkar AK, Shafiq N, Singh G, Ray P, Gautam V, Agarwal R, *et al*. Antimicrobial stewardship programs in resource constrained environments: understanding and addressing the need of the systems. Front Public Health. 2020;8:140.
25. Karadayi Y, Aydin MN, Öğrencí AS. Unsupervised anomaly detection in multivariate spatio-temporal data using deep learning: early detection of COVID-19 outbreak in Italy. IEEE Access. 2020;8:164155-77.
26. Kohnert D. On the socio-economic impact of pandemics in Africa-Lessons learned from COVID-19, Trypanosomiasis, HIV, Yellow Fever and Cholera. 2021.
27. Kokala A. The Intersection of Explainable Ai and Ethical Decision-Making: Advancing Trustworthy Cloud-Based Data Science Models. Int J All Res Educ Sci Methods. 2022;10(12):2166-83.
28. Leitmeyer KC, Espinosa L, Broberg EK, Struelens MJ, Allerberger F, Dupont Y, *et al*. Automated digital reporting of clinical laboratory information to national public health surveillance systems, results of a EU/EEA survey, 2018. Euro Surveill. 2020;25(39):1900591.
29. Lentzos F, Goodman MS, Wilson JM. Health security intelligence: engaging across disciplines and sectors. Intell Natl Secur. 2020;35(4):465-76.
30. Liu Q, Liu M, Zhou H, Yan F, Ma Y, Shen W. Intelligent manufacturing system with human-cyber-physical fusion and collaboration for process fine control. J Manuf Syst.

2022;64:149-69.
31. Luca M, Barlacchi G, Lepri B, Pappalardo L. A survey on deep learning for human mobility. ACM Comput Surv. 2021;55(1):1-44.
32. Majeed A, Hwang SO. Data-driven analytics leveraging artificial intelligence in the era of COVID-19: an insightful review of recent developments. Symmetry. 2021;14(1):16.
33. Martins KA, Ayebare RR, Bhadelia N, Kiweewa F, Waitt P, Mimbe D, *et al*. Pre-positioned outbreak research: the joint medical emerging diseases intervention clinical capability experience in Uganda. Health Secur. 2020;18(2):114-24.
34. McDermid JA, Jia Y, Porter Z, Habli I. Artificial intelligence explainability: the technical and ethical dimensions. Philos Trans R Soc A. 2021;379(2207):20200363.
35. Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan A. A survey on bias and fairness in machine learning. ACM Comput Surv. 2021;54(6):1-35.
36. Mehrdad S, Wang Y, Atashzar SF. Perspective: wearable internet of medical things for remote tracking of symptoms, prediction of health anomalies, implementation of preventative measures, and control of virus spread during the era of COVID-19. Front Robot AI. 2021;8:610653.
37. Moodley K, Rennie S, Behets F, Obasa AE, Yemesi R, Ravez L, *et al*. Allocation of scarce resources in Africa during COVID-19: Utility and justice for the bottom of the pyramid? Dev World Bioeth. 2021;21(1):36-43.
38. Murad A, Kraemer FA, Bach K, Taylor G. Probabilistic deep learning to quantify uncertainty in air quality forecasting. Sensors (Basel). 2021;21(23):8009.
39. Nadimpalli ML, Marks SJ, Montealegre MC, Gilman RH, Pajuelo MJ, Saito M, *et al*. Urban informal settlements as hotspots of antimicrobial resistance and the need to curb environmental transmission. Nat Microbiol. 2020;5(6):787-95.
40. Nguyen DC, Ding M, Pathirana PN, Seneviratne A. Blockchain and AI-based solutions to combat coronavirus (COVID-19)-like epidemics: A survey. IEEE Access. 2021;9:95730-53.
41. Nnaji ND, Onyeaka H, Reuben RC, Uwishema O, Olovo CV, Anyogu A. The deuce-ace of Lassa Fever, Ebola virus disease and COVID-19 simultaneous infections and epidemics in West Africa: clinical and public health implications. Trop Med Health. 2021;49(1):102.
42. Ojeikere K, Akomolafe OO, Akintimehin OO. A Model for Integrating Vulnerable Populations into Public Health Systems. Int J Multidiscip Res Growth Eval. 2021;20(21.2):2-393.
43. Oparah OS, Ezeh FE, Olatunji GI, Ajayi OO. Big Data-Enabled Predictive Models for Anticipating Infectious Disease Outbreaks at Population and Regional Levels. 2022.
44. O'Sullivan TM, Ramsay JD. Public health security. In: Theoretical Foundations of Homeland Security. London: Routledge; 2020. p. 208-30.
45. Palomares I, Martínez-Cámara E, Montes R, García-Moral P, Chiachio M, Chiachio J, *et al*. A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects. Appl Intell. 2021;51(9):6497-527.
46. Paramasivan A. Big Data to Better Care: The Role of AI in Predictive Modelling for Healthcare Management. Int J Innov Res Creat Technol. 2020;6(3):1-9.
47. Pratt B, Wild V, Barasa E, Kamuya D, Gilson L, Hendl T, *et al*. Justice: a key consideration in health policy and systems research ethics. BMJ Glob Health. 2020;5(4):e001942.
48. Prosperi M, Guo Y, Sperrin M, Koopman JS, Min JS, He X, *et al*. Causal inference and counterfactual prediction in machine learning for actionable healthcare. Nat Mach Intell. 2020;2(7):369-75.
49. Rahman MM, Paul KC, Hossain MA, Ali GMN, Rahman MS, Thill JC. Machine learning on the COVID-19 pandemic, human mobility and air quality: A review. IEEE Access. 2021;9:72420-50.
50. Reddy MS, Sarisa M, Konkimalla S, Bauskar SR, Gollangi HK, Galla EP, *et al*. Predicting tomorrow's Ailments: How AI/ML Is Transforming Disease Forecasting. ESP J Eng Technol Adv. 2021;1(2):188-200.
51. Reed-Berendt R, Dove ES, Pareek M; UK-REACH Study Collaborative Group. The ethical implications of big data research in public health:"big data ethics by design" in the uk-reach study. Ethics Hum Res. 2022;44(1):2-17.
52. Regmi K, Lwin CM. Factors associated with the implementation of non-pharmaceutical interventions for reducing coronavirus disease 2019 (COVID-19): a systematic review. Int J Environ Res Public Health. 2021;18(8):4274.
53. Sartorius B, Lawson AB, Pullan RL. Modelling and predicting the spatio-temporal spread of COVID-19, associated deaths and impact of key risk factors in England. Sci Rep. 2021;11(1):5378.
54. Semenza JC, Rocklöv J, Ebi KL. Climate change and cascading risks from infectious disease. Infect Dis Ther. 2022;11(4):1371-90.
55. Shi L, Stevens GD. Vulnerable populations in the United States. Hoboken: John Wiley & Sons; 2021.
56. Siegel RM, Mallow PJ. The impact of COVID-19 on vulnerable populations and implications for children and health care policy. Clin Pediatr (Phila). 2021;60(2):93-8.
57. Tang L, Zhou Y, Wang L, Purkayastha S, Zhang L, He J, *et al*. A review of multi-compartment infectious disease models. Int Stat Rev. 2020;88(2):462-513.
58. Yigitcanlar T, Mehmood R, Corchado JM. Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures. Sustainability. 2021;13(16):8952.
59. Zahid H, Shankar P. AI in Public Health: Integrating Disease Modelling and Healthcare AI for Improved Connectivity and Risk Management. 2020.
60. Zeng D, Cao Z, Neill DB. Artificial intelligence–enabled public health surveillance from local detection to global epidemic monitoring and control. In: Artificial intelligence in medicine. London: Academic Press; 2021. p. 437-53.