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Health System Resilience Modeling to Support Post-Disaster Recovery and Future Crisis Preparedness Planning

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Abstract
Health systems are frequently challenged by natural disasters, pandemics, and humanitarian crises, which disrupt service delivery, compromise infrastructure, and exacerbate population health vulnerabilities. Ensuring continuity of care and rapid recovery in such contexts requires a systematic understanding of health system resilience—the capacity to absorb shocks, adapt to changing conditions, and transform in response to crises. This presents a conceptual framework for modeling health system resilience to support post-disaster recovery and future preparedness planning. The framework integrates operational, demographic, epidemiological, and environmental data to map critical health system components, including facilities, supply chains, workforce, and utilities, and to identify potential points of vulnerability. By simulating stress scenarios and projecting service disruptions, the model provides actionable insights for optimizing resource allocation, maintaining essential services, and reducing morbidity and mortality during and after crises. Key metrics for resilience assessment include service continuity, recovery time, and health outcomes under varying disaster intensities. The framework emphasizes the use of real-time surveillance data and Internet of Things (IoT)-enabled monitoring to enable dynamic adjustments and evidence-informed decision-making. Additionally, it incorporates scenario planning to anticipate multi-hazard events and to evaluate the impact of interventions on system robustness and responsiveness. Ethical considerations, including equitable prioritization of resources and protection of vulnerable populations, are embedded in the modeling process to ensure that recommendations are socially responsible and contextually appropriate. By providing a structured approach to resilience assessment, the framework aims to support policymakers, health planners, and emergency response teams in strengthening health system preparedness, enhancing adaptive capacity, and facilitating rapid recovery post-disaster. Ultimately, the application of data-driven resilience modeling can inform strategic investments, guide multi-sectoral coordination, and foster sustainable improvements in health system performance, ensuring that populations are better protected against the increasing frequency and intensity of public health emergencies.

Keywords: Health System Resilience, Disaster Preparedness, Crisis Response, Post-Disaster Recovery, Healthcare Continuity, System Modeling, Infrastructure Robustness, Service Continuity, Workforce Capacity

1. Introduction

Health systems are inherently complex structures designed to deliver essential medical services, promote public health, and respond to emergent health needs. Despite their critical role, these systems are frequently exposed to vulnerabilities during disasters and crises, including natural hazards, pandemics, and humanitarian emergencies (Afrihyia *et al*., 2025; Taiwo *et al*., 2025). Disruptions can manifest as overwhelmed healthcare facilities, shortages of essential medicines and equipment, reduced workforce capacity, and impaired supply chain logistics. Such challenges compromise the continuity of care, delay critical interventions, and exacerbate morbidity and mortality (Okereke *et al*., 2025; Akomolafe *et al*., 2025 [20]). Evidence from recent crises, including global pandemics and large-scale natural disasters, underscores the susceptibility of health systems to both acute shocks and prolonged stresses, highlighting the need for proactive strategies to enhance system resilience (Afrihyia *et al*., 2025; Okoli *et al*., 2025).

Resilience in health systems refers to their capacity to absorb, adapt, and recover from shocks while maintaining core functions and improving preparedness for future events. A resilient health system is characterized by the ability to rapidly mobilize resources, maintain essential services, reorganize operations under stress, and learn from disruptions to strengthen future responses (Gobile *et al*., 2025; Augustine *et al*., 2025) [34, 25]. Ensuring continuity of care during crises is essential not only for immediate health outcomes but also for preserving public trust and mitigating long-term societal and economic impacts. The concept of resilience extends beyond mere recovery, encompassing anticipatory planning, adaptive capacity, and the integration of risk reduction measures into routine health system operations (Adeleke, 2025 [2]; Adeoye *et al*., 2025).

The frequency and intensity of disasters and public health emergencies have increased in recent decades due to a combination of climatic, demographic, and socio-political factors. Natural disasters such as floods, hurricanes, and earthquakes, combined with emerging infectious disease outbreaks and armed conflicts, place unprecedented demands on health systems (Okereke *et al*., 2025; Aduwo and Nwachukwu, 2025). These events often occur simultaneously or in rapid succession, challenging conventional disaster response models and underscoring the need for innovative, predictive, and data-driven planning tools (Akomolafe *et al*., 2025 [20]; Afrihyia *et al*., 2025). Health systems must therefore evolve to anticipate complex and interconnected risks, minimize service disruptions, and accelerate recovery processes.

The primary objective of this, is to develop a conceptual framework for modeling health system resilience, focusing on post-disaster recovery and preparedness for future crises. Such a framework aims to integrate system-level variables, including workforce capacity, infrastructure robustness, supply chain resilience, service delivery performance, and governance structures, into predictive models that inform planning and decision-making. By synthesizing lessons from past disasters and leveraging quantitative and qualitative modeling techniques, the framework seeks to provide policymakers, health managers, and emergency planners with actionable insights to strengthen system preparedness, optimize resource allocation, and enhance the overall resilience of health systems in the face of evolving challenges.

2. Methodology

A systematic approach was employed to identify and synthesize literature on health system resilience modeling for post-disaster recovery and future crisis preparedness. Comprehensive searches were conducted across multiple electronic databases, including PubMed, Scopus, Web of Science, and Embase, using combinations of keywords and MeSH terms such as “health system resilience,” “disaster preparedness,” “crisis response,” “modeling,” “simulation,” and “recovery planning.” Studies published in English without date restrictions were considered to capture evolving methodologies and conceptual frameworks. Reference lists of relevant articles were also screened to identify additional sources. Eligible studies included original research, reviews, and case studies that addressed the application of quantitative or qualitative modeling approaches to assess, predict, or enhance health system resilience in response to disasters or emergencies. Articles focusing solely on clinical interventions without system-level modeling, or those lacking methodological detail, were excluded. Data extraction encompassed study characteristics, modeling approaches, health system components analyzed, data sources, outcomes measured, and key findings related to resilience, recovery, or preparedness. The quality and relevance of included studies were assessed using predefined criteria adapted from established systematic review guidelines, emphasizing methodological rigor, transparency, and applicability to health system planning. Synthesized evidence informed the identification of core dimensions of health system resilience, modeling techniques, and best practices for integrating resilience considerations into post-disaster recovery and preparedness strategies. This methodology ensures a comprehensive and structured review of the literature, providing a solid foundation for developing a conceptual framework for health system resilience modeling.

2.1 Conceptual Foundations of Health System Resilience

Health system resilience is a multidimensional concept that reflects the capacity of healthcare systems to anticipate, absorb, adapt to, and recover from shocks and stressors while maintaining essential functions and improving future preparedness. Resilience encompasses three core components: absorptive capacity, adaptive capacity, and transformative capacity. Absorptive capacity refers to the system's ability to withstand immediate disruptions using existing resources and structures without significant compromise of services (Sobowale *et al*., 2025; Ojonugwa *et al*., 2025) [61, 43]. This includes the availability of contingency supplies, surge workforce arrangements, and functional infrastructure that can sustain operations during acute crises. Adaptive capacity represents the system's ability to modify processes, reallocate resources, and reorganize operations in response to evolving threats, thereby maintaining service continuity under changing conditions. Transformative capacity involves longer-term systemic changes and innovations aimed at strengthening the health system's overall structure, policies, and practices to reduce vulnerability and enhance preparedness for future crises. Collectively, these capacities define a health system's resilience trajectory, influencing both immediate outcomes during emergencies and long-term recovery potential.

Theoretical frameworks in health system resilience link structural and functional robustness to disaster outcomes, providing a foundation for modeling and intervention design. One influential perspective conceptualizes resilience as a dynamic interplay between exposure to shocks, system vulnerability, and adaptive responses. In this framework, health outcomes following a disaster are mediated by the system's inherent capacities, governance structures, resource availability, and operational flexibility. Resilience is not merely the absence of failure but a proactive, iterative process involving anticipation, mitigation, response, and learning. Systems with high resilience exhibit the ability to absorb initial shocks with minimal service disruption, adjust operations in real-time to meet changing demands, and implement transformative reforms that reduce vulnerability to future events. Empirical studies have demonstrated that health systems with robust pre-disaster planning, decentralized governance, and strong community engagement experience lower morbidity and mortality during crises and recover more rapidly (Omolayo *et al*., 2025; Damilare *et al*., 2025) [54, 27].

Several key principles underpin the conceptualization of health system resilience. Redundancy ensures the availability of backup resources, personnel, and infrastructure, enabling continuity when primary systems fail. Flexibility allows health systems to reconfigure operations, reassign staff, and modify protocols to meet emergent needs without compromising quality of care (Oloruntoba *et al*., 2025; Aduwo *et al*., 2025) [51, 13]. Responsiveness emphasizes the timeliness and appropriateness of actions taken in response to evolving threats, ensuring rapid mobilization of resources and interventions to mitigate health impacts. Robustness refers to the structural and functional strength of the system, including durable infrastructure, well-trained personnel, reliable supply chains, and resilient information systems that collectively reduce susceptibility to shocks. Integrating these principles enables health systems to maintain core functions under stress, learn from disruptions, and implement improvements that enhance long-term sustainability.

Health system resilience also incorporates cross-cutting elements such as governance, information flow, and community engagement. Effective governance structures facilitate coordination across sectors, prioritize resource allocation, and support evidence-based decision-making. Information systems enable real-time surveillance, monitoring, and early warning, allowing for anticipatory and adaptive responses. Engagement with communities ensures that interventions are contextually relevant, culturally appropriate, and supported by local stakeholders, enhancing the effectiveness and equity of crisis responses (Adeoye *et al*., 2025; Afrihyia *et al*., 2025). Furthermore, resilience is strengthened by the capacity to learn from past events through systematic evaluation, feedback loops, and the integration of lessons learned into policy and practice.

The conceptual foundations of health system resilience emphasize a multidimensional approach encompassing absorptive, adaptive, and transformative capacities. Theoretical frameworks link system robustness and functional flexibility to disaster outcomes, highlighting the dynamic nature of resilience. Key principles—redundancy, flexibility, responsiveness, and robustness—provide actionable guidance for strengthening health systems against acute and chronic shocks. Integrating governance, information systems, and community engagement ensures that resilience is operationalized effectively, enabling health systems to not only withstand crises but also to evolve, improve, and sustain essential services in the face of future challenges (Adeshina and During, 2025 [6]; Okoli *et al*., 2025). This conceptual foundation serves as the basis for developing predictive and evaluative models that guide post-disaster recovery planning and long-term preparedness strategies.

2.2 Core Components of Resilience Modeling

Modeling health system resilience requires a comprehensive understanding of the system's structure, functions, and vulnerabilities to anticipate disruptions and guide effective interventions. The core components of resilience modeling revolve around system mapping, data integration, scenario planning, and the development of quantitative metrics to assess performance under stress (Taiwo *et al*., 2025; Adeoye *et al*., 2025). Together, these components enable the identification of weaknesses, testing of response strategies, and estimation of potential outcomes in diverse crisis scenarios.

System mapping is the foundational step in resilience modeling, involving the detailed characterization of health system components and their interconnections. This process identifies critical nodes, including hospitals, clinics, supply chains, healthcare workforce, and essential utilities such as power and water systems. Mapping also considers referral networks, logistics pathways for essential supplies, and communication channels within and across health system tiers. By visualizing these components and their dependencies, modelers can pinpoint potential bottlenecks and vulnerabilities that could impair service delivery during crises (Afrihyia *et al*., 2025; Oni, 2025 [55]). Network analysis techniques are often employed to highlight nodes with the highest connectivity or the greatest potential impact if disrupted, providing a strategic focus for resilience strengthening interventions.

Integration of multiple data streams is critical for accurate and context-specific modeling. Demographic data, including population density, age distribution, and socioeconomic status, informs estimates of service demand and population vulnerability. Epidemiological data, such as incidence and prevalence of diseases, informs the potential burden of health events and guides prioritization of resources. Infrastructure data, encompassing hospital capacity, laboratory facilities, transportation networks, and utility systems, provides insight into the system's operational limits and potential points of failure (Obadimu *et al*., 2025; Umoren *et al*., 2025). Integrating these diverse datasets allows for a holistic representation of the health system, facilitating simulations that capture both the direct and indirect impacts of disruptions.

Scenario planning and stress testing form the dynamic component of resilience modeling. Models simulate various disaster and crisis scenarios, including natural hazards (e.g., earthquakes, floods), infectious disease outbreaks, and mass casualty events, to evaluate the system's response capacity. Stress testing involves applying extreme or cascading stressors to the mapped health system to observe potential breakdowns, resource shortages, or service interruptions. Scenario analyses can incorporate variations in population demand, resource availability, and environmental conditions, providing insight into the adaptive and transformative capacities of the system (Umezurike *et al*., 2025; Komi *et al*., 2025). These simulations allow policymakers and planners to assess the effectiveness of contingency plans, resource allocation strategies, and emergency protocols prior to real-world implementation.

Developing robust metrics is essential for quantifying resilience and evaluating system performance. Common indicators include service continuity, reflecting the proportion of essential health services maintained during a crisis, and recovery time, measuring the duration required for the system to return to baseline operational levels. Morbidity and mortality impacts provide direct measures of health outcomes under disruptive scenarios, capturing both immediate and downstream effects (Appoh *et al.*, 2025; Adeshina and Poku, 2025 [7]). Other potential metrics include resource utilization efficiency, patient throughput, and workforce stability. By operationalizing resilience through quantifiable measures, models can inform decision-making, guide investment in critical infrastructure, and prioritize interventions to mitigate the impact of future crises.

Core components of health system resilience modeling encompass systematic mapping of critical nodes, integration of demographic, epidemiological, and infrastructure data, scenario-based stress testing, and the development of quantitative metrics to assess system performance. System mapping identifies vulnerabilities and interdependencies, while data integration ensures realistic and context-sensitive simulations. Scenario planning and stress testing evaluate the system's absorptive, adaptive, and transformative capacities under varied conditions (Okuwobi *et al.*, 2025; Egemba *et al.*, 2025) [49, 28]. Metrics provide objective measures to assess service continuity, recovery, and health outcomes, facilitating evidence-based decision-making. Together, these components enable a comprehensive approach to modeling health system resilience, offering insights for post-disaster recovery planning, preparedness, and the development of adaptive strategies to enhance the robustness and responsiveness of healthcare systems facing future crises.

2.3 Modeling Approaches and Techniques

Effective early detection of food- and water-borne disease outbreaks relies on sophisticated modeling approaches that can integrate heterogeneous data sources, capture complex transmission dynamics, and provide actionable insights for public health interventions. Big data analytics models have evolved to combine traditional statistical methods with computational simulations, network analysis, and hybrid frameworks that incorporate both quantitative and qualitative inputs as shown in Fig 1 (Bolarinwa *et al.*, 2025; Fidel-Anyana *et al.*, 2025) [26, 33]. These approaches enable researchers and public health authorities to identify emerging outbreak signals, assess risk, and optimize response strategies in a timely and evidence-based manner.

Statistical and regression-based models are foundational tools in outbreak detection and impact assessment. These models quantify associations between environmental, demographic, and behavioral factors and the occurrence of food- and water-borne diseases. Logistic regression, Poisson regression, and generalized linear models are commonly used to estimate the probability of disease events and identify key predictors, such as contamination levels, population density, seasonal patterns, or sanitation indicators. Time-series analyses, including autoregressive integrated moving average (ARIMA) models, are particularly useful for detecting temporal trends, seasonal fluctuations, and abrupt deviations indicative of outbreak onset. Statistical models provide interpretable results and allow for hypothesis testing, making them valuable for evaluating the influence of specific risk factors and designing targeted interventions (Komi *et al.*, 2025; Umoren *et al.*, 2025). However, they may be limited in capturing non-linear dynamics and complex interactions inherent in disease transmission networks.

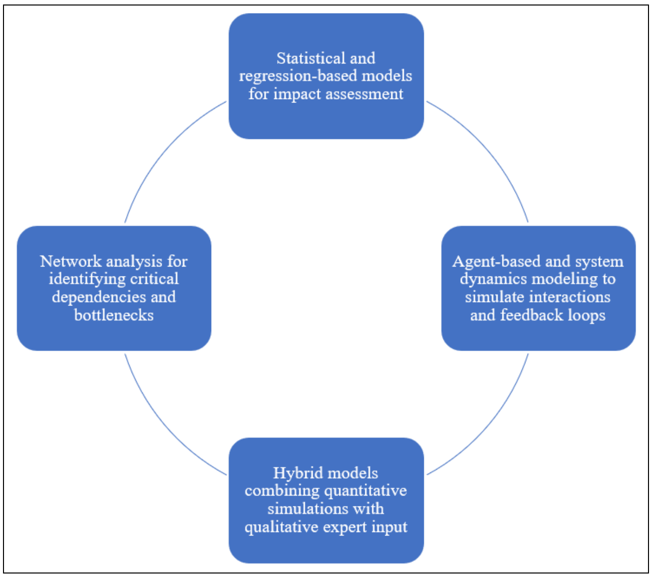

Fig 1: Modeling Approaches and Techniques

Agent-based and system dynamics modeling techniques address these limitations by simulating interactions among individual agents or system components over time. Agent-based models represent individuals, households, or institutions as autonomous entities with defined behaviors, allowing researchers to explore how local interactions and movement patterns influence disease spread. For instance, agent-based simulations can model how contaminated water sources or food distribution chains contribute to infection propagation across communities. System dynamics models, in contrast, focus on aggregated system-level feedback loops and causal relationships, capturing the dynamic interplay between public health interventions, environmental factors, and population susceptibility. Both approaches enable scenario testing, such as evaluating the impact of sanitation campaigns, vaccination programs, or regulatory inspections on outbreak mitigation (OBADIMU *et al.*, 2025; Umezurike *et al.*, 2025). These models provide insight into emergent properties that cannot be inferred from static statistical models alone, highlighting potential unintended consequences and reinforcing the importance of adaptive strategies.

Network analysis is another powerful technique for identifying critical dependencies and bottlenecks in the transmission of food- and water-borne diseases. Network models represent entities such as households, water distribution points, food supply chains, or healthcare facilities as nodes, with edges denoting interactions, flow of goods, or disease transmission pathways. By analyzing network topology, researchers can identify highly connected nodes, potential super-spreader locations, and vulnerable points where interventions may be most effective. Centrality measures, community detection algorithms, and flow analyses provide quantitative metrics to guide targeted surveillance, resource allocation, and outbreak response strategies (Enow *et al.*, 2025; Odinaka *et al.*, 2025) [29, 42]. Network analysis is particularly useful in complex urban environments or regions with interdependent food and water supply systems, where localized contamination events can have widespread downstream effects.

Hybrid modeling approaches integrate quantitative simulations with qualitative expert input to enhance predictive accuracy and contextual relevance. These models combine data-driven techniques, such as statistical regression, machine learning, or agent-based simulations, with insights from epidemiologists, environmental scientists, and public health practitioners. Expert knowledge can inform model structure, parameter selection, and interpretation of results, particularly in settings where data are sparse, incomplete, or uncertain. Hybrid models allow for iterative refinement, blending empirical evidence with domain expertise to produce forecasts that are both computationally robust and operationally actionable (Umezurike *et al*., 2025; Ozobu *et al*., 2025). They are especially valuable for assessing outbreak risk in low-resource settings or during emerging threats, where rapid decision-making is critical.

The selection of modeling techniques depends on the research objectives, data availability, and the scale of analysis. Statistical models are effective for evaluating risk factors and identifying correlations, while agent-based and system dynamics models provide mechanistic insights into disease propagation and intervention impacts. Network analysis identifies key nodes and vulnerabilities, and hybrid approaches bridge the gap between data-driven and context-informed decision-making. In practice, these techniques are often combined to leverage their complementary strengths, creating comprehensive early warning systems capable of detecting subtle signals of emerging outbreaks (Eze *et al*., 2025; Asere *et al*., 2025) [32, 24].

Modeling approaches for detecting food- and water-borne disease outbreaks encompass a spectrum of techniques ranging from statistical regression to agent-based simulations, network analyses, and hybrid models incorporating expert input. Each approach offers unique advantages in capturing different aspects of disease transmission, from identifying key predictors and temporal trends to simulating complex interactions and identifying critical dependencies. Integrating these methodologies enhances the predictive power, interpretability, and operational utility of early warning systems, enabling public health authorities to respond proactively, allocate resources effectively, and reduce the impact of outbreaks on vulnerable populations. Robust modeling frameworks are therefore central to modern surveillance systems, bridging the gap between large-scale data analytics and actionable public health interventions (Ukamaka *et al*., 2025; Sanusi, 2025) [66, 60].

2.4 Data Sources for Resilience Modeling

Effective health system resilience modeling relies on comprehensive, high-quality data that captures the operational, demographic, environmental, and real-time dynamics of the system. Integrating multiple data sources allows for accurate simulation of disruptions, stress-testing of system capacity, and informed decision-making for post-disaster recovery and preparedness planning as shown in Fig 2 (Appoh *et al*., 2025; Umezurike *et al*., 2025). These data sources provide the empirical foundation necessary to evaluate system performance and identify vulnerabilities.

Health system operational data form the backbone of resilience modeling, providing a detailed picture of the functional capacity and capabilities of healthcare facilities. This includes data on hospital and clinic bed capacity, occupancy rates, intensive care unit (ICU) availability, and availability of essential equipment such as ventilators, oxygen supply, and diagnostic tools. Staffing levels, including the number of physicians, nurses, allied health professionals, and administrative personnel, are critical for assessing the system's ability to maintain continuity of care during disruptions. Supply inventories encompassing essential medicines, vaccines, and consumables allow models to account for potential shortages under stress scenarios. Collectively, these operational datasets enable simulations that predict bottlenecks, resource deficits, and service disruptions, forming a core input for assessing absorptive and adaptive capacities (Aransi, 2025; Umoren *et al*., 2025).

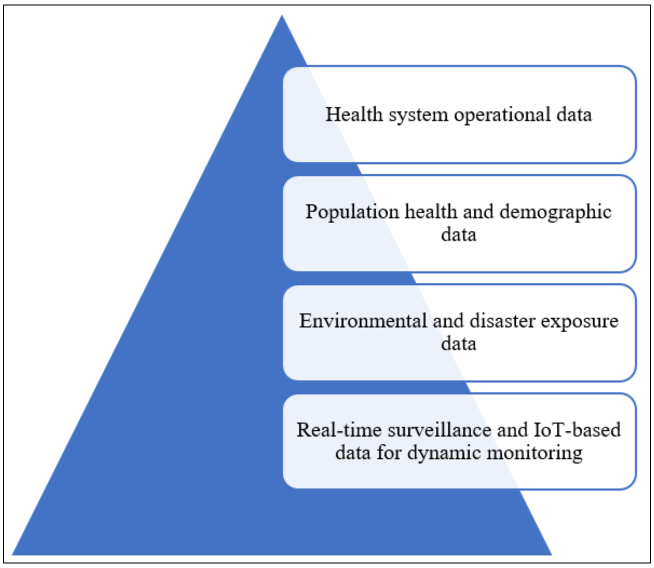

Fig 2: Data Sources for Resilience Modeling

Population health and demographic data provide insight into the demand side of health services and the vulnerability of populations to disasters and crises. Demographic variables such as age distribution, population density, household composition, and socioeconomic status inform the modeling of service demand, highlighting groups at greater risk or with higher health needs. Health indicators including disease prevalence, immunization coverage, maternal and child health metrics, and chronic disease burden further refine estimates of resource requirements under normal and crisis conditions. Incorporating population health data allows resilience models to anticipate which subgroups may experience disproportionate impacts and to prioritize interventions that enhance equity in service delivery.

Environmental and disaster exposure data are essential for modeling the external stressors that may disrupt health system functions. These data encompass historical and projected natural hazards, including earthquakes, floods, hurricanes, and extreme weather events, as well as exposure to infectious disease outbreaks and other epidemiological threats. Hazard intensity, frequency, and geographic distribution are critical for scenario planning and stress testing, allowing models to simulate localized and system-wide disruptions. Integration of climate, topographical, and infrastructural vulnerability data enables estimation of potential impacts on health facilities, supply chains, and transportation networks, informing mitigation and preparedness strategies.

Real-time surveillance and IoT-based data add a dynamic dimension to resilience modeling, enabling continuous monitoring and early detection of emerging threats. IoT devices in hospitals and clinics can track bed occupancy, equipment usage, and supply levels in real-time, while environmental sensors monitor water quality, air pollution, and weather conditions (Okereke *et al*., 2025; Omolayo *et al*., 2025 [54]). Syndromic surveillance, electronic health records, and mobile health reporting platforms provide near-real-time information on patient presentations, disease incidence, and population health trends. These real-time data streams allow adaptive modeling, facilitating rapid scenario updates and proactive decision-making during unfolding disasters.

Robust health system resilience modeling depends on the integration of multiple complementary data sources. Health system operational data capture facility capacity, staffing, and supply readiness, while population health and demographic data inform service demand and vulnerability assessments. Environmental and disaster exposure data provide context for stress scenarios, and real-time surveillance and IoT-based inputs enable dynamic monitoring and adaptive response. The convergence of these datasets creates a comprehensive and empirically grounded framework, allowing planners and policymakers to simulate system performance, identify vulnerabilities, and implement strategies to enhance resilience, ensure continuity of care, and support rapid recovery in the face of disasters and crises.

2.5 Policy and Public Health Implications

The application of resilience modeling in health and disaster management offers critical opportunities to enhance policy planning, cross-sectoral collaboration, resource allocation, and equity in public health responses. By integrating computational simulations, predictive analytics, and systems approaches into national and regional strategies, resilience modeling provides evidence-based insights that enable proactive preparation, adaptive responses, and mitigation of health impacts during disasters (Eyinade *et al*., 2025; Taiwo *et al*., 2025). The incorporation of these models into public health policy has implications for strengthening system-wide resilience, informing decision-making, and promoting equitable outcomes, particularly for vulnerable populations.

Integrating resilience modeling into national disaster management and health strategies allows policymakers to anticipate the impact of extreme events, such as floods, hurricanes, earthquakes, or pandemics, on healthcare infrastructure, service delivery, and population health. These models simulate potential scenarios, including disruptions in supply chains, hospital capacities, or critical utilities, enabling the identification of system vulnerabilities and priority intervention points. By forecasting outcomes under different disaster conditions, resilience modeling informs the design of adaptive strategies, such as scalable surge capacity, targeted vaccination or treatment campaigns, and contingency plans for high-risk regions. Embedding modeling outputs into national strategies ensures that disaster preparedness is not reactive but grounded in evidence, allowing governments to implement policies that enhance system robustness, flexibility, and recovery.

Enhancing cross-sectoral collaboration is another critical policy implication of resilience modeling. Health outcomes during disasters are influenced by factors beyond the healthcare sector, including logistics, transportation, governance, water and sanitation, and communication networks. Resilience models provide a common analytical platform for multiple sectors to coordinate planning, share data, and align strategies. For example, models can inform coordinated deployment of medical supplies, transportation of patients, and maintenance of critical infrastructure, ensuring that interdependent systems operate efficiently under stress. Cross-sector collaboration facilitated by resilience modeling strengthens institutional capacity, promotes integrated decision-making, and reduces duplication of efforts, which is particularly important in large-scale or multi-hazard disasters.

Supporting evidence-based resource allocation and emergency preparedness is a further advantage of resilience modeling. By quantifying risks, potential impacts, and system bottlenecks, models provide policymakers with actionable insights for prioritizing investments and deploying resources effectively. Health authorities can use modeling outputs to optimize hospital bed allocation, pre-position medical supplies, schedule personnel deployment, and identify high-risk populations requiring preventive interventions. Such evidence-based planning reduces inefficiencies, enhances response speed, and minimizes avoidable morbidity and mortality. Resilience modeling also allows continuous evaluation and refinement of preparedness plans, ensuring that policies remain responsive to changing environmental, demographic, and health system conditions (Adeshina, 2025; Jimoh and Omiyefa, 2025 [36]).

Promoting equity in access to care during and after disasters represents an essential public health and ethical consideration. Vulnerable populations—including low-income communities, marginalized ethnic groups, rural residents, and people with chronic conditions—are disproportionately affected during emergencies. Resilience models can incorporate social determinants of health, geographic accessibility, and population vulnerabilities to identify disparities in service availability and predict differential health outcomes. Policy interventions guided by these insights can prioritize equitable distribution of resources, establish mobile clinics or telehealth services in underserved areas, and tailor emergency response strategies to address the needs of at-risk populations. By embedding equity considerations into modeling and planning, governments and health agencies can mitigate the disproportionate impact of disasters and enhance social justice in health outcomes.

Resilience modeling has significant implications for public health policy and disaster management. Integrating modeling outputs into national strategies enables proactive, evidence-based planning and enhances the capacity of health systems to respond to extreme events. Cross-sectoral collaboration supported by modeling fosters coordinated decision-making, efficient resource allocation, and robust operational responses. Furthermore, resilience modeling provides a framework for addressing inequities in access to care, ensuring that interventions during and after disasters reach vulnerable populations. By translating complex simulations into actionable policy guidance, resilience modeling strengthens health system resilience, informs emergency preparedness, and supports equitable, efficient, and adaptive responses to both natural and human-made hazards, ultimately improving population health outcomes and societal well-being (Taiwo *et al*., 2025; Olufemi *et al*., 2025 [52]).

2.6 Challenges and Limitations

Modeling health system resilience for post-disaster recovery and future crisis preparedness presents a range of challenges and limitations that must be carefully considered to ensure reliable and actionable outputs (Olisa, 2025 [50]; Adeshina, 2025). These challenges arise from data constraints, the inherent uncertainty of disaster scenarios, the technical complexity of modeling approaches, and ethical considerations in decision-making as shown in Fig 3. Recognizing these limitations is critical for developing realistic frameworks and for guiding policymakers and health system planners in interpreting model outputs responsibly.

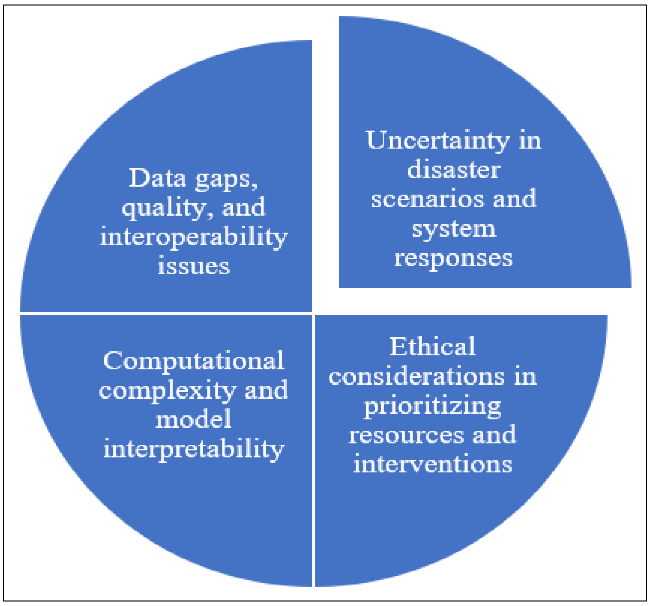

Fig 3: Challenges and Limitations

A primary challenge lies in data gaps, quality issues, and lack of interoperability across health system information sources. Health facility data, including bed capacity, staffing, and supply inventories, are often incomplete, inconsistently reported, or outdated, limiting the accuracy of resilience models. Population health and demographic data may be collected infrequently or at coarse geographic resolutions, making it difficult to capture localized vulnerabilities and high-risk subpopulations. Environmental and disaster exposure data can also be sparse or unevenly distributed, particularly in low- and middle-income countries where meteorological and hazard monitoring systems may be underdeveloped. Moreover, interoperability between different datasets—such as electronic health records, public health surveillance systems, and infrastructure databases—is frequently limited, requiring extensive data cleaning, harmonization, and standardization. These limitations can introduce biases and uncertainties into model outputs, affecting the reliability of scenario analyses and policy recommendations.

Uncertainty in disaster scenarios and health system responses constitutes another significant limitation. Disasters, whether natural hazards, pandemics, or complex humanitarian emergencies, are inherently unpredictable in their timing, magnitude, and geographic scope. Modeling must account for a wide range of potential scenarios, including cascading system failures, population displacement, and supply chain disruptions. However, the stochastic nature of these events makes precise forecasting challenging, and resilience models may over- or under-estimate system vulnerability. Additionally, human behavior, including healthcare-seeking patterns, compliance with emergency measures, and community adaptation strategies, adds further variability that is difficult to quantify accurately in predictive models.

Computational complexity and model interpretability present additional challenges. Health system resilience models often integrate multiple layers of data, including operational, demographic, environmental, and real-time surveillance streams, resulting in high-dimensional, data-intensive simulations. Advanced analytical approaches such as agent-based modeling, systems dynamics, or machine learning algorithms can generate detailed predictions but may require substantial computational resources and specialized expertise. Moreover, complex models may produce outputs that are difficult for policymakers and stakeholders to interpret, potentially limiting their practical utility. Balancing model sophistication with usability and transparency remains a persistent challenge in applied resilience modeling.

Ethical considerations are critical in the development and application of resilience models, particularly when prioritizing resources and interventions. Models may identify certain populations, facilities, or regions as high-risk, raising questions about equitable allocation of limited resources during crises. Decisions informed by modeling must carefully weigh potential trade-offs, ensuring that vulnerable groups are not systematically disadvantaged. Ethical challenges also extend to data use, including the protection of sensitive patient and community information, informed consent for data collection, and the responsible communication of model uncertainties to decision-makers (Ozobu *et al*., 2025; Eyinade *et al*., 2025).

While health system resilience modeling is a powerful tool for informing post-disaster recovery and preparedness, it faces significant challenges and limitations. Data gaps, quality issues, and interoperability constraints can reduce model accuracy, while inherent uncertainties in disaster scenarios and system responses complicate prediction. Computational complexity and limited interpretability can hinder practical application, and ethical considerations must guide resource allocation and data use. Addressing these challenges requires careful methodological design, transparent reporting, stakeholder engagement, and continuous refinement to ensure models provide actionable insights while respecting equity and ethical standards.

2.7 Future Directions

The field of resilience modeling for disaster preparedness and public health is rapidly evolving, driven by advances in computational methods, data availability, and digital health infrastructure. Future directions focus on enhancing predictive capabilities, improving real-time monitoring, maintaining model adaptability, and expanding the scope of analyses to address increasingly complex disaster scenarios (Sala *et al*., 2025; James *et al*., 2025) [59, 35]. These innovations aim to strengthen health system resilience, optimize resource allocation, and promote equitable responses in the face of diverse hazards.

Incorporation of artificial intelligence (AI) and machine learning into resilience modeling represents a major advancement for predictive capabilities. AI algorithms can analyze large, heterogeneous datasets, including historical disaster impacts, environmental conditions, population demographics, healthcare utilization, and infrastructure vulnerability. Machine learning models can identify non-linear relationships, hidden patterns, and early indicators of system stress, providing more accurate predictions of disaster impacts on health outcomes and service delivery. Such predictive analytics enable proactive intervention planning, including targeted deployment of medical resources, prioritization of high-risk populations, and optimization of emergency response strategies. Over time, AI can improve model precision by learning from previous disaster events, thereby enhancing both situational awareness and strategic planning.

Real-time dashboards offer another transformative opportunity, allowing dynamic monitoring and early warning of emerging crises. By integrating streaming data from environmental sensors, health information systems, transportation networks, and social media, dashboards provide decision-makers with up-to-date insights into evolving conditions. Real-time visualization of key metrics, such as hospital occupancy, infection rates, or water contamination levels, enables rapid identification of hotspots, detection of system bottlenecks, and timely activation of emergency protocols. These platforms can also support scenario simulation and resource optimization, facilitating coordinated responses across multiple sectors and jurisdictions.

Continuous model updating with new disaster and health data streams is critical for maintaining relevance and accuracy. Disasters are inherently dynamic, and health system vulnerabilities can shift rapidly due to population changes, infrastructure development, or environmental alterations. Incorporating real-time epidemiological, environmental, and logistical data into resilience models ensures that predictions remain valid under changing conditions. Iterative updating also allows models to learn from recent events, enhancing their ability to anticipate impacts, evaluate intervention effectiveness, and refine preparedness plans (Adikwu *et al*., 2025; Osamika *et al*., 2025) [10, 56]. This continuous learning process strengthens both operational and strategic decision-making, reducing the risk of outdated assumptions or misallocated resources.

Expanding models to account for compound crises and multi-hazard scenarios represents an important frontier in resilience modeling. Many regions face overlapping threats, such as concurrent floods and disease outbreaks or earthquakes compounded by water contamination. Traditional single-hazard models may underestimate risk and fail to capture cascading effects across health, infrastructure, and social systems. Multi-hazard modeling incorporates interactions between simultaneous events, feedback loops, and cumulative impacts, providing a more comprehensive understanding of vulnerabilities and potential outcomes. This approach supports integrated emergency planning, prioritization of interventions, and identification of critical interdependencies that may otherwise be overlooked.

The future of resilience modeling for disaster preparedness and health systems lies in leveraging AI and machine learning, implementing real-time dashboards, continuously updating models with new data, and expanding analyses to encompass compound crises and multi-hazard scenarios. These directions enhance predictive accuracy, operational responsiveness, and system adaptability, enabling health authorities to anticipate and mitigate the impacts of disasters more effectively. By integrating advanced computational methods, dynamic monitoring, and comprehensive scenario planning, resilience modeling can support evidence-based, equitable, and proactive public health interventions, ultimately strengthening the capacity of communities and health systems to withstand and recover from a wide range of disasters (Adebowale, 2025 [1]; Komi *et al*., 2025).

3. Conclusion

Health system resilience modeling plays a critical role in supporting post-disaster recovery and enhancing preparedness for future crises. By systematically mapping health system components, integrating demographic, epidemiological, and infrastructure data, and simulating a range of disaster scenarios, resilience models provide actionable insights into vulnerabilities, recovery capacities, and resource needs. These models allow policymakers and health planners to anticipate potential disruptions, identify critical nodes within the system, and implement targeted interventions that maintain continuity of care and reduce morbidity and mortality during emergencies. The evidence-based, data-driven nature of resilience modeling ensures that decisions are guided by quantifiable risk assessments and predictive analyses rather than intuition or reactive measures, thereby strengthening overall system robustness and responsiveness.

The application of such modeling frameworks also emphasizes the value of scenario planning and stress-testing health system functions. Metrics derived from these analyses, including service continuity, recovery times, and health outcome impacts, provide measurable indicators of system performance and resilience. This approach not only informs immediate post-disaster responses but also guides long-term investments in health infrastructure, workforce development, and emergency preparedness planning. Furthermore, integrating real-time surveillance and IoT-based monitoring enhances the capacity to dynamically assess system status during crises, supporting adaptive management and rapid decision-making.

The development and implementation of resilience models require a multidisciplinary approach, drawing expertise from public health, epidemiology, data science, systems engineering, and policy planning. Collaboration across sectors, including healthcare providers, government agencies, and community stakeholders, ensures that models are contextually relevant, operationally feasible, and aligned with local priorities. Investment in modeling capacity, data infrastructure, and analytical training is essential to sustain and expand the utility of resilience frameworks, particularly in regions prone to frequent natural disasters, pandemics, or humanitarian emergencies.

Health system resilience modeling constitutes a foundational tool for enhancing post-disaster recovery and future crisis preparedness. By leveraging data-driven insights, promoting evidence-based decision-making, and fostering multidisciplinary collaboration, these frameworks enable health systems to anticipate risks, optimize resource allocation, and improve population health outcomes. Strategic investment in modeling capacity and continuous refinement of methodologies will further strengthen health system resilience, ensuring that communities are better protected against the growing challenges posed by disasters and public health crises.

4. References

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