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A Hierarchical Consilient Algorithm for Epidemic Risk Prediction within the One Health Framework

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Abstract: Emerging and re-emerging infectious diseases increasingly arise from the interaction of ecological disruption, human and animal health, social vulnerability, infrastructure fragility, and collective behavior. Although the One Health paradigm has strengthened interdisciplinary thinking, many operational frameworks still aggregate heterogeneous risk factors without clearly distinguishing their causal position. This article proposes a hierarchical consilient algorithm for epidemic risk prediction within the One Health framework. The model differentiates primary structural drivers, secondary mediators and amplifiers, and epidemiological outcomes, thereby translating complex multidimensional risk into a more interpretable and actionable structure. The proposed framework is intended to support early warning, preparedness, prioritization of interventions, and adaptive surveillance, particularly in fragile, conflict-affected, and environmentally stressed settings.

Keywords: One Health, epidemic intelligence, early warning systems, concausality, epidemic risk, fragile settings, artificial intelligence, public health preparedness.

INTRODUCTION

In recent years, the One Health approach has become a central conceptual and operational framework for addressing global health threats. It recognizes that the health of humans, animals, plants, and ecosystems is closely linked and interdependent [1] (World Health Organization, 2023). The approach is particularly relevant for zoonotic and epidemic-prone diseases, where pathogen emergence is shaped not only by biological mechanisms but also by environmental degradation, climate change, land-use transformation, urbanization, food insecurity, human mobility, and institutional fragility.

The value of One Health lies in its capacity to overcome disciplinary fragmentation. However, the practical translation of this paradigm into early warning and preparedness remains challenging. Many frameworks identify a broad set of interconnected determinants but do not always clarify which factors operate as root causes, which act as mediators or amplifiers, and which represent downstream epidemiological outcomes.

This article proposes a hierarchical consilient algorithm for epidemic risk prediction within the One Health framework. The objective is not to reduce epidemic complexity to a rigid linear sequence, but to organize interacting determinants according to their causal depth, systemic function, and operational relevance. In this perspective, complexity is not denied; it is structured.

The central hypothesis is that interdisciplinary risk frameworks can become more predictive and actionable when they incorporate a causal hierarchy. Territorial ecological vulnerability may be treated as a primary structural driver, while factors such as human–animal proximity, weak surveillance, low vaccination coverage, food insecurity, population displacement, institutional mistrust, and fragile infrastructure may function as secondary mediators or amplifiers. Their interaction may then lead to epidemiological outcomes such as spillover, outbreak emergence, delayed response, rapid transmission, and increased morbidity and mortality.

The article therefore positions the proposed model at the intersection of One Health, epidemic intelligence, early warning systems, and predictive analytics. It argues that preparedness should not be limited to the collection of multidisciplinary data but should also include tools capable of interpreting the progressive formation of risk.

BACKGROUND AND STATE OF THE ART

The One Health Approach

One Health is defined by the World Health Organization as an integrated and unifying approach that aims to sustainably balance and optimize the health of people, animals, and ecosystems (World Health Organization, 2023). It mobilizes multiple sectors and disciplines to address health threats at the human–animal–environment interface, including emerging infectious diseases, antimicrobial resistance, food safety, and environmental degradation.

The One Health Joint Plan of Action developed by FAO, UNEP, WHO, and WOAH further emphasises the need for coordinated governance, data systems, capacity building, and integrated action to prevent, predict, detect, and respond to health threats [2] (Food and Agriculture Organization of the United Nations et al., 2022). These priorities confirm the importance of moving from conceptual interdisciplinarity to operational preparedness.

Epidemic Intelligence and Early Warning Systems

Epidemic intelligence refers to the systematic collection, verification, analysis, and interpretation of information from multiple sources to detect, assess, and respond to public health risks. Early Warning, Alert and Response Systems are designed to identify outbreak signals before they become difficult to control, particularly in emergencies and fragile contexts (World Health Organization, 2023a).

WHO's EWARS model illustrates the importance of rapid surveillance in humanitarian emergencies, where conflict, displacement, weak infrastructure, and limited access to health services increase the risk of infectious disease transmission [3] (World Health Organization, 2023a). Climate-informed early warning systems also show that environmental and meteorological variables can improve the timeliness and impact of disease control by supporting action before the epidemic curve accelerates [4](World Health Organization, 2021).

Despite these advances, early warning systems often depend on data quality, timeliness, interoperability, and institutional response capacity. Their effectiveness may be limited when surveillance is fragmented, health systems are weakened, or social and behavioral variables are insufficiently integrated.

Digital Tools, GIS, Big Data, Machine Learning, and AI

Geographic Information Systems, Big Data, machine learning, and artificial intelligence have expanded the capacity to integrate heterogeneous data streams for infectious disease surveillance and forecasting. These tools can identify spatial clusters, detect anomalies, analyze environmental and mobility patterns, and support predictive modelling for outbreak risk [5] (Santangelo et al., 2023).

However, technological sophistication alone does not guarantee actionable prevention. Predictive models may remain incomplete if they aggregate variables without clarifying their causal role. For this reason, computational approaches should be embedded in frameworks that distinguish structural drivers, mediating mechanisms, and epidemiological outcomes.

Fragile and Conflict-Affected Settings

Fragile and conflict-affected settings represent a critical test case for One Health and early warning frameworks. In these contexts, epidemic risk emerges from the convergence of political instability, destroyed infrastructure, weak surveillance, forced displacement, food insecurity, low vaccination coverage, limited access to safe water, and disrupted health services.

These settings show that epidemics are rarely caused by a single factor. Instead, they emerge from a layered system of vulnerabilities. A hierarchical model can therefore help identify which factors constitute deep structural exposure and which mechanisms transform exposure into outbreak risk.

Mental Health, Trust, and Collective Behaviour

Psychosocial and behavioral variables are often underrepresented in epidemic prediction. Yet trust in institutions, risk perception, stigma, misinformation, collective stress, vaccine confidence, and adherence to preventive measures can strongly influence the effectiveness of outbreak control.

Within the proposed framework, these dimensions are treated as secondary factors or mediators. They do not necessarily create structural exposure, but they may accelerate, delay, or intensify the transformation of vulnerability into epidemiological impact.

PROPOSED HIERARCHICAL CONCAUSALITY ALGORITHM

Rationale and Aim

The proposed algorithm organizes epidemic risk through three analytical levels: primary structural drivers, secondary mediators and amplifiers, and dependent epidemiological outcomes. This hierarchy does not imply a simplistic linear causality. Rather, it provides an interpretive architecture for understanding how multiple determinants interact across ecological, social, institutional, and biological systems.

Primary Drivers

Primary drivers are structural root causes that create the conditions under which epidemic risk may emerge. They include environmental degradation, biodiversity loss, deforestation, climate stress, unplanned urbanization, water insecurity, human–animal interface intensification, health system collapse, and infrastructure fragility.

Table 1 presents the ecological-systemic progression through which biodiversity, resource availability, environmental conditions, and ecological dynamics may shift from stability to crisis. In this framework, epidemic risk is interpreted not as an isolated event but as the outcome of a progressive loss of coherence between life systems, resources, ecological niches, and social organization.

Table 1: Conceptual framework describing the progression of ecological and systemic conditions across sequential stages, from pre-cyclical environmental drivers and the emergence of biological complexity to biodiversity expansion, crisis dynamics, potential collapse, recovery pathways, and long-term resilience. The table links biodiversity patterns, energy and resource availability, environmental conditions, ecological dynamics, and resulting system outcomes.

Stage	Biodiversity Pattern	Energy and Resources	Environmental Conditions	Ecological Dynamics	System Outcome
Pre-cyclical phase	Natural cycles create recurring variations.	Solar radiation and climatic phases provide energy inputs.	Light/darkness, day/night, and seasonal rhythms shape conditions.	Cycles regulate opportunities for biological activity.	Conditions become favorable for the emergence and development of life.
Ground Zero	Early biological complexity begins to emerge.	Physical energy is converted into chemical energy.	Organic compounds accumulate in primitive environments.	Aggregation reactions support more complex structures.	The primordial soup creates the basis for biological evolution.
1	Biodiversity increases.	Energy and resources support adaptation.	Life spreads across available environments.	Ecological balance develops through diversification.	Resilient factors support the expansion and stabilization of life.
2	Many species coexist.	Energy and nutrients are sufficient and accessible.	Diverse environments sustain multiple forms of life.	Ecological niches are filled and differentiated.	System stability allows social and biological development.
3	Species diversity declines and biodiversity is reduced.	Energy and nutrients become insufficient or unevenly distributed.	Environments are degraded by stressors such as pollution.	Ecological niches are reduced or eliminated.	System coherence weakens, marking the onset of crisis.
4	One species may spread excessively or become dominant.	Energy use occurs at the expense of environmental balance.	Altered environments increase pathogen spillover risk.	Incompatible niches contribute to conflict and instability.	Social crisis, epidemics, and systemic disruption may emerge.
5	Few species remain.	Energy availability becomes poor or unreliable.	Environments become hostile to life.	Generalized degradation affects ecological structures.	Life is placed at risk, with possible extinction outcomes.

Recovery pathway	Biodiversity begins to regenerate.	Resources are redistributed more sustainably.	Environmental restoration improves living conditions.	Ecological niches are gradually rebuilt.	The system may return to a more balanced and resilient state.
Long-term balance	Diversity and adaptation remain dynamic.	Energy flows are managed within ecological limits.	Environmental pressures are monitored and mitigated.	Ecological and social systems remain interconnected.	Resilience depends on coherence between life, resources, and environment.

Secondary Mediators and Amplifiers

Secondary factors mediate or amplify the effects of primary drivers. They include low vaccination coverage, weak adherence to preventive measures, mistrust of institutions, misinformation, stigma, collective stress, poor public communication, limited access to care, and social inequalities. These variables influence whether structural vulnerability remains latent or becomes an active epidemic threat.

The operational logic of the algorithm is summarized in Figure 1: **assess** risk determinants, **plan** intervention priorities, **implement** prevention actions, and **optimize** the model through continuous updating of data and observed outcomes.

Figure 1: Operational workflow of the hierarchical concausality algorithm for epidemic risk prediction within the One Health framework. The four-step process—Assess, Plan, Implement, and Optimise—summarizes how risk determinants are identified, intervention priorities are defined, preventive actions are implemented, and the model is continuously updated through new data and observed outcomes.

Epidemiological Outcomes

Epidemiological outcomes are dependent variables, resulting from the interaction between primary and secondary factors, as shown in Figure 2. They include pathogen spillover, outbreak emergence, transmission acceleration, delayed diagnosis, delayed institutional response, increased morbidity, increased mortality, and reduced effectiveness of control measures.

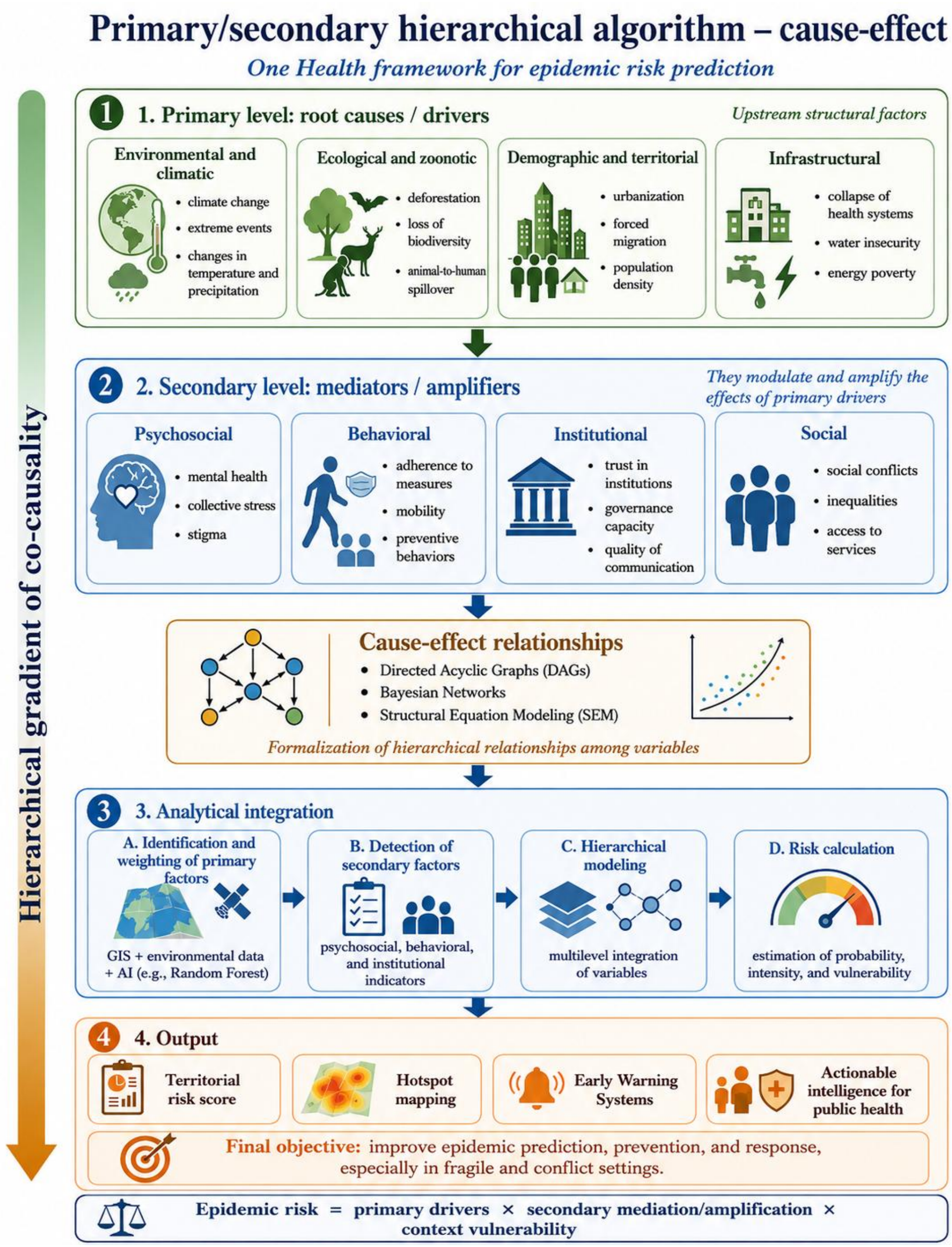

Figure 2: Hierarchical concausality algorithm applied to the One Health framework for epidemic risk prediction. The model links primary structural drivers, secondary mediators and amplifiers, contextual vulnerability, and epidemiological outcomes to support prevention, surveillance, and health response planning.

Analytical Formalization

The conceptual hierarchy can be formalized through causal modelling tools such as directed acyclic graphs, Bayesian networks, structural equation modelling, or machine learning pipelines with interpretable feature weighting. These methods can help clarify which variables are upstream determinants, which operate as mediators, and which represent measurable outcomes [6] (Greenland et al., 1999;) [7] (VanderWeele, 2015).

OPERATIONAL STEPS OF THE ALGORITHM

- **Step 1: Assess.** The first step identifies primary structural drivers through environmental, epidemiological, infrastructural, climatic, and territorial data. Geographic Information Systems (GIS), satellite data, health system indicators, and ecological metrics can support the identification of high-risk areas.
- **Step 2: Plan.** The second step integrates secondary mediators and amplifiers, including behavioral, psychosocial, institutional, and community-level variables. The objective is to determine which vulnerabilities are most likely to transform structural exposure into outbreak risk.
- **Step 3: Implement.** The third step translates risk assessment into intervention priorities. Risk may be classified as low, medium, or high. Low risk may require routine monitoring; medium risk may require intensified surveillance and community engagement; high risk may require immediate preventive action, including vaccination campaigns, water and sanitation interventions, targeted communication, and psychosocial support.
- **Step 4: Optimize.** The fourth step consists of a feedback loop. As new data become available, the model updates risk estimates and recalibrates causal weights. This makes the algorithm adaptive rather than static, allowing it to respond to changes in cases, mobility, institutional capacity, misinformation, and community adherence.

The flowchart in Figure 1 summarizes the four operational phases of the algorithm: assessing risk determinants, planning intervention priorities, implementing prevention actions, and optimizing the model through the continuous updating of data and observed outcomes.

PRACTICAL APPLICATION: POST-CONFLICT INFORMAL URBAN AREA

A post-conflict informal urban area provides a useful example of the proposed framework. Primary drivers may include destroyed water and sanitation networks, overcrowding, interrupted vaccination programmes, population displacement, and limited health infrastructure. These conditions create a favorable environment for pathogen circulation and reduce the capacity for early detection.

Secondary factors may include mistrust in authorities, collective trauma, stigma, misinformation, and low adherence to preventive measures. Their interaction with primary structural drivers can increase the probability of outbreak emergence, diagnostic delay, and uncontrolled transmission.

From Risk Factors to Measurable Variables

For algorithmic implementation, each factor should be translated into observable and, where possible, measurable variables. Deforestation may be measured through forest-cover loss; water insecurity through access indicators; health system vulnerability through facility density and workforce availability; institutional trust through survey or behavioral indicators; and vaccine hesitancy through uptake data and community feedback.

Contribution to Epidemic Risk Assessment

The model contributes to epidemic risk assessment by clarifying not only where risk is high, but why it is forming. This distinction supports more targeted interventions. A territory where risk is driven mainly by water insecurity requires a different response from one where risk is driven by low adherence, misinformation, or institutional mistrust.

DISCUSSION

The main strength of the proposed model is its ability to organize epidemic risk determinants according to causal depth and operational relevance. By distinguishing primary drivers from secondary mediators and epidemiological outcomes, the framework avoids treating all variables as equivalent. This may improve the interpretability of risk assessments and support more precise public health decisions.

Operationally, the algorithm could complement existing surveillance platforms rather than replace them. It may strengthen preparedness strategies by adding a causal layer to current data systems, helping decision-makers identify the most relevant intervention points in specific territories.

The model is particularly relevant for fragile and conflict-affected settings, where epidemic risk is generated by overlapping vulnerabilities. In such contexts, hierarchical classification can support prioritization among water and sanitation measures, vaccination campaigns, surveillance reinforcement, public communication, community engagement, and psychosocial support.

Limitations and Conditions for Applicability

The model requires reliable, updated, and comparable data. In fragile contexts, data collection may be discontinuous or incomplete. For this reason, the algorithm should be considered a progressive and adaptable framework that requires empirical validation, piloting, and calibration in different epidemiological and territorial settings.

Future Development

Future development should focus on building a prototype capable of integrating environmental, epidemiological, infrastructural, behavioral, and social data. Pilot studies in vulnerable urban areas, post-conflict territories, and regions exposed to ecological stress would allow the model to be tested, refined, and adapted. Integration with existing surveillance systems could then strengthen early warning, risk communication, and public health preparedness.

CONCLUSION

This article has proposed a hierarchical concausality consilient algorithm for epidemic risk prediction within the One Health framework. The model responds to the need to move beyond descriptive aggregation of risk factors by distinguishing primary structural drivers, secondary mediators and amplifiers, and epidemiological outcomes.

The proposed framework aims to make epidemic complexity more interpretable and operational. By translating heterogeneous determinants into a structured causal architecture, it may support more targeted prevention, earlier warning, adaptive surveillance, and context-sensitive intervention planning.

Further empirical validation is required. However, the model offers a theoretical and operational basis for strengthening interdisciplinary preparedness in a world where epidemic risk increasingly emerges from the interaction of environmental disruption, social vulnerability, institutional fragility, and human behaviour.

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THEORETICAL WORKS AND MONOGRAPHS

The generally-oriented content discussed in this article—concerning the origin and evolution of living systems, the phenomenology of living organisms, and the development of complex systems—is inspired by the following works, which are cited as references.

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