Technical Solutions for Risk Assessment and Emergency Response of Sudden Major Zoonotic Disease Outbreaks: Based on Machine Learning

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Abstract. Recent data from the World Health Organization (WHO) underscores that approximately 75% of reported global diseases are zoonotic, posing dual threats to both livestock industries and human health. Establishing an epidemic risk prediction model is imperative, leveraging cutting-edge technologies such as blockchain, artificial intelligence, and big data. This paper aims to devise emergency response strategies for major public health crises, vital for fortifying government prevention capabilities. It outlines plans to develop an epidemic risk assessment model, align emergency responses with TOPSIS evaluations, and implement an OODA (Observe, Orient, Decide, Act) emergency response framework. Additionally, the study investigates enhancing epidemic emergency measures in China through the integration of contemporary internet knowledge. By bridging theory with practice and leveraging advanced technologies, this research contributes to the development of comprehensive strategies for combating zoonotic diseases and safeguarding public health on a global scale.

Keywords: zoonotic diseases; risk assessment; emergency response; machine learning; artificial intelligence

1 Introduction

Sudden public health crises, like the ongoing COVID-19 outbreak, are hard to unpredictable, rapidly spreading, and have far-reaching impacts, posing serious threats to human lives. Over the past three decades, infectious diseases like SARS, H5N1, Ebola, MERS, and Zika have surged, presenting significant challenges globally. With 75% of recent diseases being zoonotic, originating from animals, there's growing concern about their socio-economic repercussions. Animal epidemics not only harm the livestock industry but also endanger human health. This has led to increased focus on research for governing, preventing, and controlling such crises, reflecting their paramount importance in global public health. Recent environmental changes have profoundly altered ecosystems, reshaping interactions among humans, animals, and the environment. With many recent public health crises originating from animals, concerns about emerging zoonotic diseases are growing. Studies reveal shortcomings in human responses to

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epidemics, highlighting the need for improved prevention and control measures. It's clear that addressing epidemics requires systemic approaches beyond just biomedical and technical aspects. This study advocates for comprehensive epidemic risk assessments, innovative response mechanisms, and a global perspective to address the socio-economic implications effectively. Such efforts are crucial for enhancing public health security and hold both theoretical and practical significance.

2 Advantages and Disadvantages of Past Technical Paths

Research on sudden and widespread animal outbreaks encompasses four main domains:

Firstly, studies focus on major public health crises such as the SARS outbreak in China in 2003 and the COVID-19 pandemic in 2019, driving research on epidemic prevention, emergency mechanisms, and management strategies. Scholars have extensively examined epidemic prevention and control capabilities, explored emergency response mechanisms, and refined management systems to enhance preparedness and response .[1][2][3]

Secondly, research examines the prevention and control capacities against sudden epidemics, highlighting challenges such as the use of non-scientific strategies, inadequate technological support, and a lack of awareness among stakeholders [11]. Despite commendable progress in epidemic prevention and control in China, grassroots level issues persist, including limited resources, insufficient training, and outdated methods.[4][5][6]

Thirdly, studies review animal epidemic emergency mechanisms, emphasizing the importance of establishing scientifically rigorous monitoring systems and ensuring timely reporting and verification processes at grassroots levels.[9] Effective monitoring networks, appropriate techniques, data analysis, and early warning systems are integral to proactive surveillance and containment efforts.[7][8]

Lastly, research consolidates studies on animal epidemic emergency management, noting China's transition to a comprehensive, institutionalized, and security-oriented approach, influenced by successful containment of SARS and foreign models emphasizing risk analysis, traceability, and effective emergency recovery procedures.[10][14] International studies underscore the significance of robust emergency regulations, risk analysis systems, and traceability mechanisms in managing animal epidemics.

Existing research offers valuable insights but also has limitations: Firstly, theoretical studies on epidemic control often list problems with scattered, qualitative policy recommendations, necessitating deeper, comprehensive research. Secondly, research on epidemic risk estimation tends to be vague, lacking systematic inquiry and innovative quantitative approaches. Thirdly, research on epidemic risk prediction operates on a single-level analysis, lacking integration and systematic examination. Lastly, achievements in public health, management, and communication studies are fragmented, with limited integration.This study aims to bridge the gap between quantitative research and qualitative analysis by constructing a risk prediction model grounded in epidemic theories. Leveraging technologies like blockchain, AI, and big data, it seeks effective emergency response measures for major public health crises. Enhancing government capacity in epidemic prevention and control is crucial for national security.

3 The Technical Path and Application Model Constructed in This Paper

China faces significant public crises, notably intensified by the COVID-19 pandemic. Prioritizing epidemic risk assessment and enhancing preventive measures are crucial for safeguarding public health, reinforcing national security, and mitigating economic and social disruptions. This project, aligned with national imperatives, integrates theoretical research, interdisciplinary approaches, and advanced technology to investigate risk assessment and emergency management in major public health crises in China. Figure 1 depicts the comprehensive framework of this research effort.

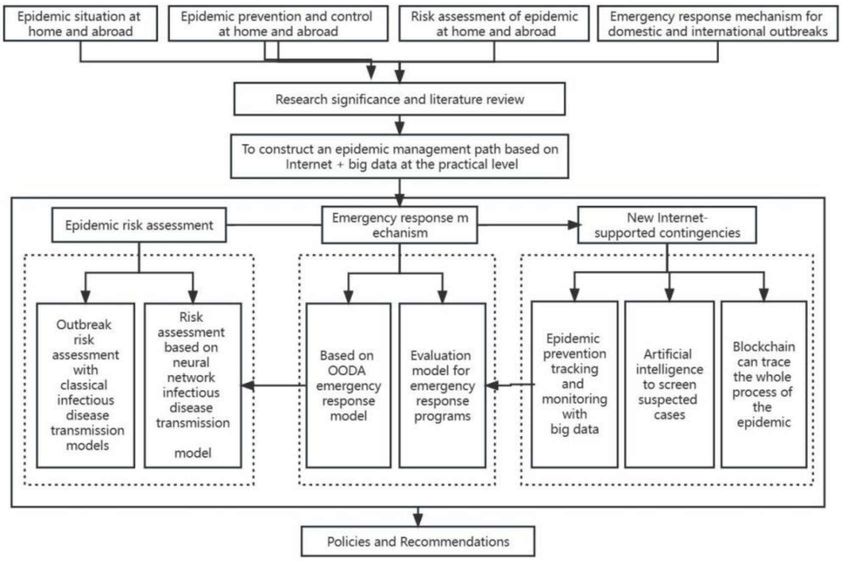

Figure 1: Research framework

This paper outlines three primary research objectives. Firstly, it aims to develop an epidemic risk assessment model by delving into the dynamic nature of epidemic transmission and its stochastic evolution. Secondly, it delineates an emergency response plan based on the epidemic risk assessment model, utilizing the TOPSIS evaluation model to identify optimal actions and establishing the OODA emergency response mechanism. Lastly, it examines challenges and causal factors in animal epidemic emergency management in China, aiming to enhance government measures through integrating internet-based knowledge.

This paper tackles two key scientific challenges. Firstly, it addresses the need to develop epidemic risk assessment models. While significant progress has been made in researching infectious disease transmission models, challenges persist. The conventional SEIR model, for instance, relies on basic transmission numbers, leading to debates over parameter allocation and discrepancies in results. Moreover, many studies overlook the impact of complex network factors like media coverage and government interventions on transmission dynamics. Hence, constructing an effective epidemic transmission model is both crucial and daunting.

The second challenge involves crafting a dynamic emergency response model suited to the evolving demands of epidemic control. This necessitates a sophisticated system capable of swift observation, judgment, decision-making, and action. Adapting emergency strategies in real-time based on epidemic severity presents a complex task. Evaluating multiple contingency plans quantitatively to determine the most effective one poses a central challenge. Additionally, establishing an Internet-supported emergency framework for inter-departmental and inter-agency collaboration adds further complexity to this research endeavor.

4 Research Routes, Experimental Methods and Key Technologies

This paper outlines research methods, beginning with the utilization of LSTM and FSEIR models to construct a risk estimation model. Subsequently, the TOPSIS method will establish an evaluation model for emergency response schemes, while the OODA analysis method will guide epidemic emergency response mechanisms. Content analysis will compile and assess animal epidemic emergency management cases. Additionally, an anthropological perspective and data mining techniques will unveil individual-level narratives and strategies, ensuring micro-level considerations are not overlooked.

This study advocates for interdisciplinary research to predict risks and emergency responses to abrupt epidemic events effectively. It emphasizes multidisciplinary, multiperspective, and scientifically informed inquiries to enhance management mechanisms. Utilizing the LSTM-FSEIR method, the research constructs an epidemic risk prediction model, followed by a comprehensive analysis of risk prediction's interaction with emergency measures. This culminates in developing a dynamic TOPSIS-OODA model for addressing animal epidemic emergencies. Drawing from domestic and international practices, the study proposes measures to enhance China's management of major animal epidemics.

5 Construction and development of the model

China faces a heightened state of public crises due to the COVID-19 pandemic, impacting various aspects of the nation. Improving epidemic risk assessment and prevention measures is crucial for safeguarding public health, enhancing national security, and mitigating the pandemic's economic and social impacts. This project aligns with national imperatives, utilizing existing theoretical frameworks, interdisciplinary approaches, and advanced science and technology to thoroughly investigate risk assessment and emergency management strategies for major public health emergencies in China.

Therefore, the construction steps proposed in this paper can be roughly divided into the following six steps:

Step 1 entails a thorough examination of existing theoretical research, encompassing a critical review of domestic and international efforts. This involves exploring key concepts and theories related to major animal epidemics, risk prediction, epidemic prevention and control, and emergency management. Foundational principles and terminology in these areas will be rigorously interpreted and analyzed.

Step 2 entails a comparative analysis focusing on Western developed nations to evaluate the feasibility of adopting their practices and theories. This includes examining their frameworks for animal epidemic risk assessment, epidemic emergency response mechanisms, and implemented strategies. The goal is to assess their potential relevance and applicability in the Chinese context.

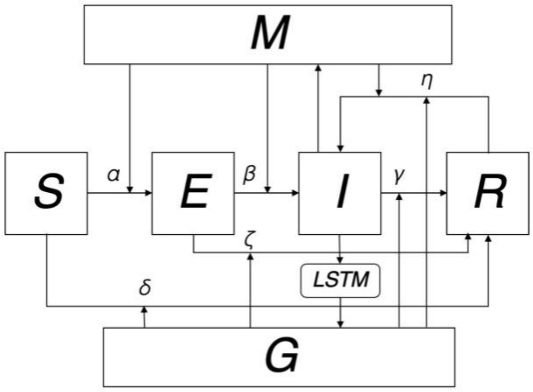

Figure 2: LSTM-FSEIR infectious disease model

Step 3 involves developing an epidemic risk assessment model crucial for accurately evaluating epidemic intensity and progression, guiding the selection of effective emergency response strategies. Adopting the LSTM-FSEIR model, we enhance the conventional SEIR framework by incorporating Media (M) and Government intervention (G). Illustrated in Figure 2, media transmission influences infection rates, while government measures affect immunity

and recovery rates. This dynamic model introduces a feedback mechanism to capture epidemic dynamics comprehensively. Detailed parameters are outlined in Table 1.

Table 1: List of model parameter definitions

Parameters	Definitions	Parameters	Definitions
S	Susceptible	α	Rate of Spread
E	Latent	β	Transformation Speed
I	Infected	γ	Removal Rate
R	Recovered	δ	Direct Immunization Rate
M	Media Communications	ε	Immunization Rate
G	Government Prevention and Control	η	Recurrence Rate

The FSEIR model is defined in the form of equation (1), where dS/dt 、 dE/dt 、 dI/dt 、 dR/dt shows the change rate of the proportion of susceptible, latent, infected and recovered persons over time respectively. The media report spread model is defined as in Equation (2), where $\alpha(0)$、 $\beta(0)$、$\eta(0)$ represents the initial transmission rate, initial conversion rate, and initial recurrence rate, and M represents media spread. The government prevention and control model is defined as Eq. (3), where $\zeta(0)$、$\delta(0)$、$\gamma(0)$ represents the initial immunization rate, direct immunization rate, and removal rate, respectively, and G represents the government's prevention and control efforts.

$$\begin{cases} \frac{dS}{dt} = -\alpha(t)SI - \zeta(t)S \\ \frac{dE}{dt} = \alpha(t)SI - \beta(t)E - \delta(t)E \\ \frac{dI}{dt} = \beta(t)E - \gamma(t)I + \eta(t)R \\ \frac{dR}{dt} = \zeta(t)S + \delta(t)E + \gamma(t)I - \eta(t)R \end{cases} \tag{1}$$

$$\begin{cases} M = I \\ \alpha(t) = \alpha(0) + M \\ \beta(t) = \beta(0) + M \\ \eta(t) = \eta(0)M \end{cases} \tag{2}$$

$$\begin{cases} \zeta(t) = \zeta(0) + G \\ \delta(t) = \delta(0) + G \\ \gamma(t) = \gamma(0) + G \\ \eta(t) = \eta(0) - G \end{cases} \tag{3}$$

LSTM neural network is often used in the predictive analysis of time series problems [12] and the prediction of infectious diseases [13]. In this study, LSTM is used to predict the number of infected persons in the epidemic. The sequence of the number of infected persons I changing over time was expressed as $I(t)(t = 0,1,2,\cdots N)$, and the number of infected persons$I(t+1)$could be predicted by the infected persons at the three time nodes $I(t-2), I(t-1), I(t)$, as shown in Formula (4), where $I^{\wedge}(t+1)$ represents the predicted value of the infected persons at the time by $lstm$ neural network. The spread of the epidemic can be roughly divided into three stages: free transmission, transition and control.

During the free transmission stage, people are unaware of the epidemic's danger, and activities proceed as usual without government intervention. In the control stage, stratified prevention measures are implemented based on the number of infections. The expression of prevention and control strength G is shown in Equation (5). In the free spread stage of the epidemic, when the number of infected people is less than the threshold x, the prevention and control strength is 0. When the number of infected people exceeds the threshold x, the government will take prevention and control measures y.

$$I^{\wedge}(t+1) = lstm\left[I(t-2)、I(t-1)、I(t)\right] \tag{4}$$

$$G = \begin{cases} I^{\wedge}(t+1) \leq x, 0 \\ I^{\wedge}(t+1) > x, y \end{cases} \tag{5}$$

Step 4 involves examining the Emergency Response Mechanism for major public health emergencies. These emergencies are lethal, difficult to treat, and can rapidly escalate if not promptly managed. A structured response mechanism is essential to control such epidemics within a limited timeframe and area. This study analyzes the epidemic response process using the OODA framework (Observe, Orient, Decide, Act) and develops an epidemic emergency response model, as depicted in Figure 3.

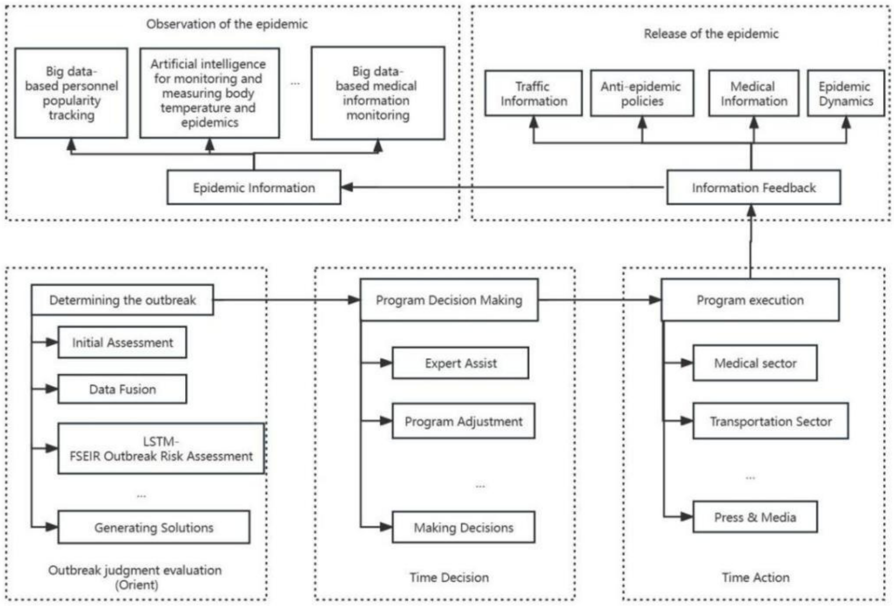

Figure 3: Decision models for emergency response to major zoonotic disease outbreaks

Figure 3 illustrates the OODA closed-loop model, facilitating real-time planning and adjustment of emergency response methods based on evolving epidemic situations. This enhances the effectiveness of emergency prevention and control. However, with multiple action plans in emergency response, evaluating and selecting the best plan is crucial. The TOPSIS emergency response plan evaluation model is integrated into the decision stage of the OODA model to address this task. The model assumes that there are n plans to be evaluated, and the positive matrix$X$composed of m evaluation indexes is shown in Formula 6. It is normalized (as in formula 7) and the matrix Z is normalized as in formula 8. The maximum value Z^+ (formula 9) and minimum value Z^- (formula 10) are defined, and the distance between the $i, i \in (1,2,\cdots,n)$ evaluation object and the maximum value is defined as D_i^+ (formula 11) and the minimum value D_i^-. Then, the normalized score of the ith evaluation object is S_i, and max (S_i) is marked as the current optimal emergency response scheme.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \vdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{7}$$

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \vdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix} \tag{8}$$

$$\begin{gathered} Z^+ = (Z_1^+, Z_2^+, \cdots, Z_m^+) \\ = (max\{z_{11}, z_{21}, \cdots, z_{n1}\}, max\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \end{gathered} \tag{9}$$

$$\begin{gathered} Z^- = (Z_1^-, Z_2^-, \cdots, Z_m^-) \\ = (min\{z_{11}, z_{21}, \cdots, z_{n1}\}, min\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \end{gathered} \tag{10}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(Z_j^+ - z_{ij}\right)^2} \tag{11}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(Z_j^- - z_{ij}\right)^2} \tag{12}$$

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{13}$$

Step 5: Utilizing New Internet Technologies for Emergency Response.In the digital age, combating epidemics demands data-driven solutions. Beyond establishing predictive models and enhancing decision-making processes, leveraging the latest Internet tools—such as big data, AI, and blockchain—is essential. Blockchain facilitates population tracking and data integrity, ensuring effective monitoring. AI aids in swift case identification, bolstering community efforts. Big data enables real-time data sharing, supporting precise monitoring and policy implementation. This empowers governments to strengthen prevention, streamline verification, and provide data-backed strategies, enhancing overall epidemic control.

Step 6: Policy Recommendations: In the digital era, epidemic control relies on leveraging big data and the Internet. We advocate for an "Internet + big data" framework, utilizing machine learning to glean insights from diverse data sources. These insights bolster risk prediction and emergency management for animal epidemics in China, guiding government strategies and system design.

6 Conclusion

In summary, this research provides a meticulously constructed framework for addressing the intricate challenges posed by major zoonotic disease outbreaks, with a specific focus on the contemporary context in China. The comprehensive exploration of the theoretical landscape underscores the authors' commitment to grounding their approach in a deep understanding of key concepts related to risk prediction, epidemic prevention, and emergency management. Through a cross-national comparative analysis, the paper intelligently evaluates the applicability of foreign practices within the unique Chinese context, showcasing a thoughtful and nuanced approach to synthesizing global insights. The pivotal contribution of this research lies in the development of the LSTM-FSEIR epidemic risk assessment model. By expanding upon the traditional SEIR framework and incorporating additional components such as Media and Government intervention, the model demonstrates a sophisticated understanding of the intricate dynamics of epidemic transmission. The utilization of the Long Short-Term Memory Neural Network further enhances the model's predictive capabilities, ensuring a scientifically robust foundation for risk assessment. Furthermore, the proposed emergency response mechanism, rooted in the OODA loop and augmented by the TOPSIS evaluation model, showcases a logical and adaptive decision-making process. The integration of real-time dynamic planning, continuous observation, and a quantitative evaluation model reflects a commitment to evidence-based emergency response strategies. The paper's forward-thinking approach is particularly evident in its advocacy for leveraging new internet technologies. The proposal to integrate big data, artificial intelligence, and blockchain in an emergency measures platform is grounded in a nuanced understanding of their potential applications. The emphasis on blockchain for traceability and tamper resistance, AI for swift case identification, and big data for comprehensive information sharing positions the model at the forefront of technological innovation in epidemic prevention and control. Lastly, the call for a policy framework in the digital realm, specifically the fusion of the Internet and big data, underscores a commitment to data-driven decision-making. By advocating for machine learning capabilities to provide continuous insights, the authors bridge the gap between theoretical constructs and practical, responsive strategies. This holistic and meticulously crafted approach, grounded in rigorous theoretical foundations and embracing cutting-edge technologies, marks a significant contribution to the scientific discourse on epidemic prevention and control, particularly in the face of evolving zoonotic threats.

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