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ORIGINAL RESEARCH

A Big Data and FRAM-Based Model for Epidemic Risk Analysis of Infectious Diseases

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Purpose: The use of multi-source precursor data to predict the epidemic risk level would aid in the early and timely identification of the epidemic risk of infectious diseases. To achieve this, a new comprehensive big data fusion assessment method must be developed.

Methods: With the help of the Functional Resonance Analysis Method (FRAM) model, this paper proposes a risk portrait for the whole process of a pandemic spreading. Using medical, human behaviour, internet and geo-meteorological data, a hierarchical multi-source dataset was developed with three function module tags, ie, Basic Risk Factors (BRF), the Spread of Epidemic Threats (SET) and Risk Influencing Factors (RIF).

Results: Using the dynamic functional network diagram of the risk assessment functional module, the FRAM portrait was applied to pandemic case analysis in Wuhan in 2020. This new-format FRAM portrait model offers a potential early and rapid risk assessment method that could be applied in future acute public health events.

Keywords: epidemic risk, FRAM, model, big data portrait

Introduction

Epidemics of infectious diseases in urban areas not only cause widespread infection, morbidity and death in a population but also cause panic and social disorder, which seriously affect the normal production and life of the affected population.[1] In recent decades, the scale and frequency of urban infectious diseases have increased; examples include SARS (2002), Swine Flu (2009), Ebola (2014), MERS (2015), Zika (2016) and COVID-19 (2019/2024).[2] Therefore, it is critical to recognize and control the risk of urban infectious disease outbreaks and ensure that cities are prepared for infectious diseases.[3]

Pandemics have a wide range of complicated and overlapping effects. Thus, risk evaluation and response policies become the key processes in risk prevention and control systems. However, in the process of the prevention of the COVID-19 pandemic, health administrations like the CDC made improper risk judgments and inappropriate response decisions, leading to ineffective risk prevention and control. This caused certain losses and resulted in substantial impacts on the social economy and the health and lives of the population. This exposed weaknesses and loopholes in the current epidemic risk awareness and governance.

As a result of emerging communication technologies such as big data, artificial intelligence and the Internet of Things, early and rapid risk assessment has gradually become an important part of the governance of public health emergencies. Given the uncertainty of emerging infectious diseases, with more extensive and timely data collection, we will be able to better capture danger signals of emerging infectious disease outbreaks in a timely manner. This would help in performing early risk assessments of emerging infectious disease outbreaks.[4]

In the current domestic big data environment, there is not yet an established process or methodology for the risk profiling of infectious disease outbreaks, there is a lack of identified precursor information on the risks of infectious disease outbreaks, and it is difficult to provide comprehensive coverage rate of emerging infectious diseases. This has resulted in the current low early risk prediction capability. The Function Resonance Analysis Method (FRAM) is a risk-accident evolution model that analyses the public safety system from a global perspective.[5] FRAM can be used to study

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the interactions and connections between functional aspects of a system, analyse potential adverse factors leading to public health events, and study the coupling and propagation of risk due to functional heterogeneity.[6] Therefore, using the FRAM model, this study constructed a reasonable and effective risk portrait process for infectious disease outbreaks and attempted to use the user portrait theory to describe and analyse the big data of urban infectious diseases. The ultimate goal of this research was to provide a more scientific and effective basis for the judgment of the risks of infectious disease outbreaks and the decision-making for prevention and control systems.

Theory and Question

Risk Analysis of Epidemics

Risk analysis is a methodology for systematically organizing scientific and technical information and its uncertainties to answer specific questions about risk. In order to fully realize risk management and ensure social stability, analysts adopt a combination of qualitative and quantitative methods to recognize the risk of an acute public health event and analyse the uncertainty of this event's possible occurrence or development. Through risk analysis, the likelihood of the occurrence of an event, the scope of the population involved in the risk, the severity of the risk, and the extent of the ensuing changes can be more accurately estimated. Thus, a decision can be made on whether or not to take effective countermeasures to prevent and defuse the crisis.

Risk Analysis Objectives

With the growing complexity of the urban infectious disease risk analysis environment, it has become increasingly difficult to meet the current needs of epidemic prevention and control with manual experience-based analysis of risk object attributes, types, quantities, threats, etc. Further, the long-term accumulation of precursor information contains a wealth of evidence for improved analysis.[7] In order to achieve realistic regulation of risk analysis, urban infectious disease outbreak risk assessment objectives are proposed based on the temporal dimension of the risk governance assessment process.

Firstly, the short-term goal: speed and accuracy. Short-term refers to the early stage of the emergence of risk precursors; there is a need to quickly and accurately grasp the epidemic risk situation. On the one hand, under the pressure of risk evolution and proliferation, it is necessary to quickly identify risk precursors and judge the risk situation; on the other hand, due to the requirements of subsequent risk prevention and control measures, it is necessary to achieve targeted identification and accurate study and judgment.

Secondly, the medium-term goal: tracking prediction. This is the middle period in the whole cycle of an epidemic, from risk gestation to the end of the epidemic under specific time and space regulations. The single life cycle of an urban infectious disease epidemic can include multiple stages, such as risk gestation, risk transformation, epidemic outbreak, situation development, trend attenuation and epidemic end. In each stage, epidemic risk analysis is the basis for the design and implementation of prevention and control policies. Therefore, this analysis must not only ensure immediacy but must be also forward-looking.

Finally, the long-term goal: crisis learning. Long-term refers to the historical pulse line formed by the occurrence of an infectious disease epidemic and possible future epidemics. These epidemic events together constitute the case base of risk prevention and control of infectious disease epidemics. Each risk analysis process must be learning-oriented; successful experiences must be absorbed, lessons with actual epidemic characteristics must be learned from failures.

Risk Analysis Procedure

The risk analysis of infectious disease epidemics refers to the use of the theory and method of early risk assessment to identify the risk precursor signals of an infectious disease epidemic in the early stage of its occurrence, analyse the risk of the infectious disease, predict the possible epidemic risk level, and determine whether a corresponding early warning signal is issued. Epidemic risk analysis mainly uses the multi-source data fusion method to combine various types of qualitative and quantitative monitoring data. By exploring and integrating information of different types and from different sources, "full sample" risk analysis data from different government departments, medical institutions and social organizations can be scientifically processed and a comprehensive analysis of the infectious disease epidemic risk can be performed.

By setting up a reasonable and effective risk analysis process for infectious diseases, the assessment work can be performed in an orderly manner according to established steps. This will improve the efficiency and technical level of the risk assessment of infectious diseases. Moreover, this can restrict the rights of administrative systems and public suspicion can be eliminated through the use of procedural justice. From this specific analysis flow in Figure 1, it can be seen that, three stages from risk perception to risk comprehension, and to risk evolution also include data layer, information layer and knowledge layer, leading to the final judgement.

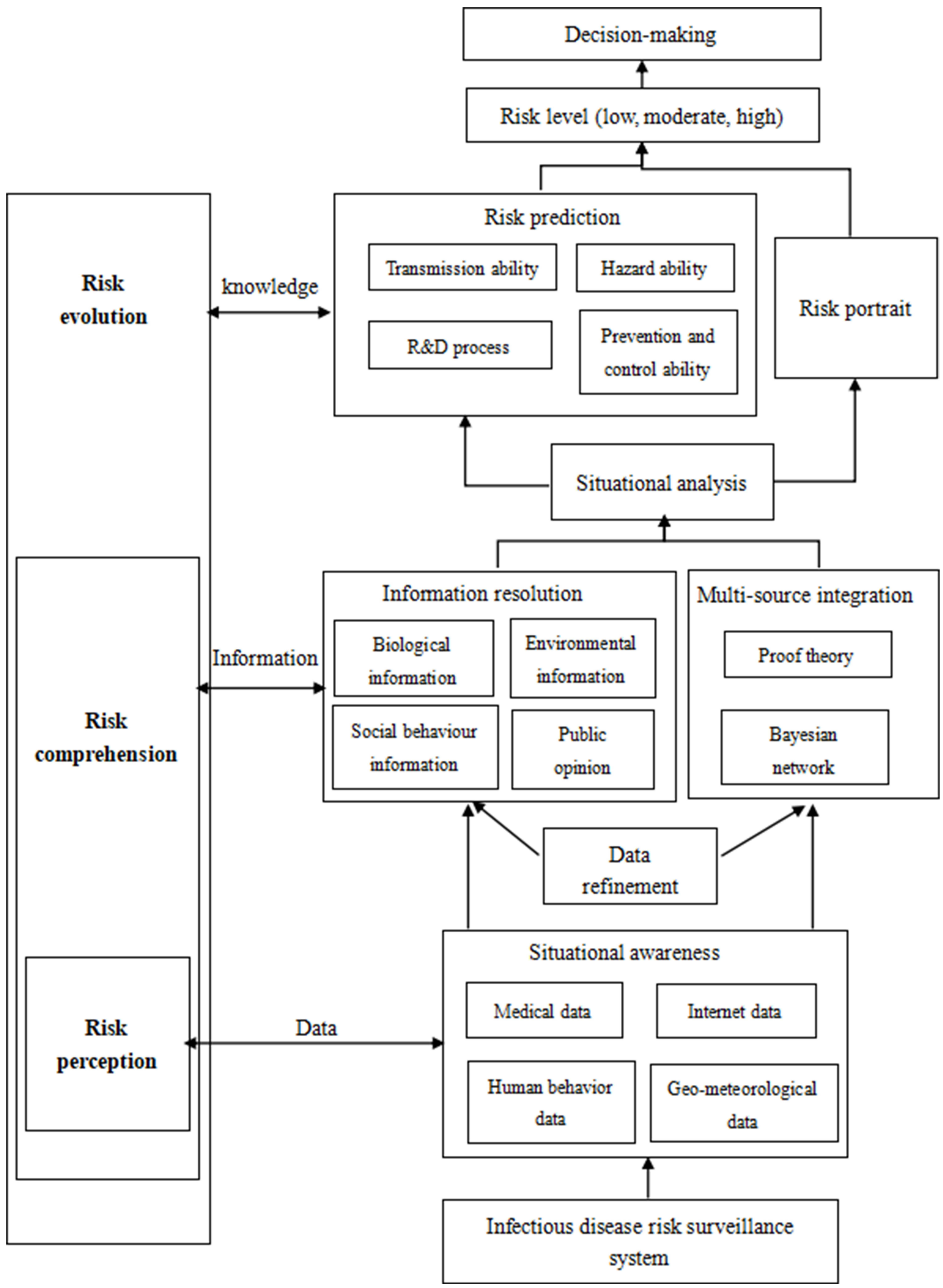

Figure 1 Risk analysis process for infectious diseases.

At the data level, different types of precursor information are monitored through the infectious disease epidemic risk monitoring system, and preliminary risk awareness is obtained. At the information level, according to the obtained risk precursor information, different methods are used to analyse and refine the data, and then, an in-depth risk understanding is obtained. At the knowledge level, based on the information analysis, data fusion and related risk assessment methods, the risk transmission ability, hazard ability, vaccine development process, and prevention and control ability are comprehensively analysed and transformed into corresponding knowledge, so as to predict the risk, and finally, make an appropriate judgement.

Risk Analysis Model

Many epidemic risk models have been developed in recent years. However, due to the variation in the richness of information at different risk stages, there can be a lack of adaptability in the research models and risk misjudgement can occur. As shown in Table 1, firstly, the early evaluation model: through the monitoring and analysis of the precursor information of the epidemic risk of infectious diseases, the epidemic risk is preliminary identified.[8] Secondly, the situation awareness model: identification of the early warning signals becomes key analytic point to conduct epidemic risk situation awareness. Thirdly, the data fusion model: this is suitable for monitoring data from a variety of different systems and environmental information sources, including text, video and other types of data. It uses multi-source data fusion methods such as evidence theory to evaluate the overall risk level and to construct a Bayesian network to quantitatively predict the spread of the epidemic risk. Fourthly, the comprehensive analysis model: based on the previous risk analysis, the multi-source feature portrait is developed for the risks in different time periods in a certain area. This provides an understanding of the dynamic evolution characteristics of the epidemic risk and helps the epidemic prevention and control policymakers gain a comprehensive understanding of the risk situation.

Among them, the situation awareness model can be roughly divided into three levels. Situation perception is the data collection and processing stage. Here, precursor information on the risk of the infectious disease is collected and a comprehensive perception of the infectious disease is obtained. The main technologies used in situation perception include communication infrastructure, big data technology, GIS technology, medical security technology and so on.[9] Situation comprehension is the stage of data fusion. Experts are invited to fuse the precursor information in the situation awareness stage through expert knowledge and related technologies. This provides a deep understanding of the data.

Risk Portrait

The concept of user portrait was first proposed by Alan Cooper in 1998. He argued that the essence of a user portrait is a labelled portrait that is abstracted from the user's statistical information, preference habits, social network and consumption behaviour. It is a true portrayal of people using information and a comprehensive model that reflects the real situation of users.[10] The continuous development of information technologies provides technical support for the realization of user portrait theory. Based on this portrait theory, the goal is no longer limited to the user, but to the risk, and the risk data are used to realize the portrait of the risk. Risk portrait is a method of obtaining and analysing the relevant precursor information of an event risk through all kinds of data, classifying the risk to understand different risk states, and conducting a risk judgment. Relatedly, studies of the transportation industry have monitored big data in relation to trucks, including the driving trajectory, speed, fatigue when driving and other data, and have developed risk portraits of trucks to assess risk levels and effectively reduce the occurrence of risks.[11]

Table 1 Risk Analysis Models and Corresponding Risk States

Risk Analysis Model	Data Feature	Risk States
Early evaluation model	Signs of an abnormality	Monitoring the precursor information
Situation awareness model	Low data relevance	Partial precursor information warning
Data fusion model	High data relevance	Unclear risk orientation
Comprehensive analysis model	Comprehensive data	Clear characterization and comprehensive analysis

FRAM

Function Resonance Analysis Method (FRAM) is a system approach based on the Safety-II perspective proposed by Hollnagel. This method was developed based on Hollnagel's research on accident causation theory in 2004. FRAM can be used to demonstrate and analyse how design steps and task management are performed through multiple functions and activities.[12] Moreover, FRAM is primarily used to determine how certain parts of a task and a set of operations typically occur. The model can be used to explain a selected event or performance in terms of the functions required to perform the activity, the potential coupling between the functions, and the general variability of the functions. In the context of the current study, in order to effectively perform an epidemic assessment, it is necessary to understand the connectivity variability between individuals and organizations, individuals and systems, and organizations and systems. FRAM was also used in this study because it can explain sequential causes and causality in a complex and conceptual way. As such, FRAM is suitable for accident-cause analysis and risk assessment for complex organizational-technical, human-technical, and organizational-human relationships.[13]

The first step of using FRAM to analyze the system risk of accident evolution mechanism is to identify and describe the basic functions of the system, transform the system into functional modules, and use six attributes such as I, O, P, R, T and C to describe and characterize each functional module. To this end, the functional module definition of FRAM will be redefined according to the characteristics of the disease such as the number of infected people in the epidemic, the risk of interpersonal contact, and the preventive measures such as vaccination and wearing masks, as shown in Figure 2.

Next, it is necessary to analyze the potential changes of each functional module. It is not only necessary to pay attention to the internal changes of the system, but also to analyze the impact of external factors on functional changes. Analyze how the system functions are coupled and how the coupling affects the downstream function modules through the upstream function modules. In order to reveal the risk evolution of infectious disease outbreaks, it is necessary to draw the FRAM function oscillation network diagram to predict the future epidemic risk situation.

The last step is to analyze the results of FRAM functional resonance, find out the reasons leading to the spread of epidemic risk, and put forward improvement measures to control the outbreak and pandemic based on weak functional links.

Research Question

The transformation of urban spatial structure by use of Spatiotemporal big data has changed the thinking paradigm and our traditional response approach to public health emergencies. The FRAM model can be used to study the interactions and connections between the functional links of a system, analyse the potential adverse factors leading to public health events and study the risk coupling and propagation caused by functional variation.[14] This study attempted to link the FRAM model, user portrait theory and the big data characteristics of urban infectious disease epidemics. Through multi-source fusion big data, a reasonable and effective risk portrait for infectious disease epidemics was constructed. Using big data portraits to form risk portraits of urban infectious disease epidemics, real-time dynamic and accurate risk

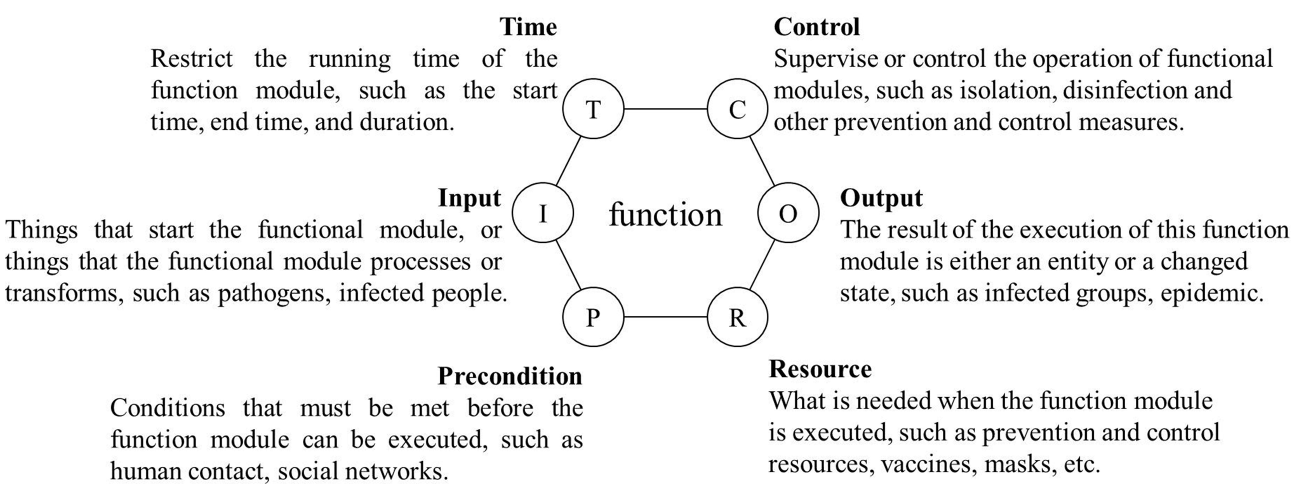

Figure 2 Six aspects of characterizing FRAM function.

assessment of an infectious disease can be achieved. These findings offer a more effective scientific basis for the prevention and control decision-making of urban infectious disease epidemic risks.

Methods Design

To date, FRAM has been applied in different settings and has been used to analyse different activities in healthcare, including to improve emergency care, understand the transition of care for COPD patients between municipal governments and hospitals,[15] for sepsis management, and as an input for anticoagulation management guidelines in two countries.[16] FRAM provides insights into how front-line hospital staff can adapt to the current work environment with limited resources. It can also be used to develop clinical guidelines and procedures and to design clinical processes. Ann-Therese used FRAM to map hospital discharge, revealing the coupling and interdependence between different individuals, teams and organizations, as well as the most vulnerable points when patients arrive home.[17] To address the increased complexity of manufacturing leading to potential occupational health and safety (OHS) and operational risks, Alimeh adopted a new method that integrated FRAM and system theory process analysis (STPA) to analyse the OHS and operational risks of assembly in Industry 4.0.[18] Mariam used FRAM to map the referral process from the perspective of resilience engineering and adopted value stream map (VSM) to map the referral process from a lean perspective.[19] Through collaborative use of FRAM and VSM methods, potential quality improvement measures were identified. This, in turn, improved the referral process.

Procedure for Epidemic Risk Assessment

In this section, a hybrid method that combines FRAM and risk portrait is proposed for the risk assessment of infectious disease outbreaks. First, FRAM was used to describe the process of infectious disease risk assessment. Then, the functional module that outputs the risk assessment results was identified. Subsequently, it was labelled, and finally, the functional module was dynamically analysed based on the risk evolution process, thereby achieving the goal of a risk portrait. The research framework shows the four main research steps.

Step 1: FRAM modelling. In order to perform the assessment work according to the established steps in an orderly manner, improve the efficiency and technical level of infectious disease risk assessments, limit the rights of administrative structures, and use procedural justice to eliminate public doubts, a reasonable and effective infectious disease risk analysis process was established. Figure 2 presents the specific risk function definition chart using FRAM. This work is different from previous risk research and judgment processes.

Step 2: Function module labelling. According to the FRAM model established in step 1, the single function module that outputs the risk assessment results was extracted and analysed. In order to better analyse this functional module, the functional module was labelled and qualitatively analysed based on three aspects: Basic Risk Factors (BRF), the Spread of the Epidemic Threats (SET) and Risk Influencing Factors (RIF).

Step 3: Risk situation analysis. Dynamic analysis of the labelled function module was carried out. Δt was set as the unit change time, and the obtained multi-source data (such as Newly confirmed cases, population flow data, Baidu keyword index, network hot search data, transportation convenience and air temperature data) were used to analyse the following time points:t, Δt, $t+2\Delta t$ and $t+3\Delta t$. Then, the t functional module chart was drawn.

Step 4: Result of risk assessment. The general formula for the risk assessment in this paper was *Risk=possibility×consequence*. In the previous risk mapping step, the risk of infectious diseases was evaluated and described through FRAM. The functional module that outputs the risk assessment results was identified and labelled. A dynamic analysis of this functional module was conducted according to the risk evolution process to form multi-dimensional evidence of multivariate data fusion. Finally, the risk level was rated based on the multi-dimensional risk portrait.

Function Module Labeling

In order to develop a risk portrait, a dynamic analysis of the single module of the infectious disease risk assessment in the FRAM model was performed. It was first necessary to label this module. Function module labelling is a method to classify and identify function modules. The label can be understood as a description or identification of the function module to help users better understand and use the functional module. The label can be a short description of the module's functionality or a description of its usage scenarios. In this study, the label for the functional module of the infectious disease outbreak risk was designed into BRF, SET and RIF, as shown in Figure 3.

BRF refers to the specific factors that cause a certain adverse outcome or state of an event or system in risk management. In infectious disease outbreaks, basic risk factors can include population movements, environmental pollution, climate change, public health facilities, and inadequate health education and vaccination. These have significant impacts on the spread and progress of the outbreak.

SET refers to the risk of transmission of the outbreak; that is, the possibility of the infectious disease spreading through different routes. In epidemic prevention and control work, effective measures should be taken to contain the chain of transmission to prevent the spread of the epidemic.

RIF refers to the factors that may influence an event or action to have an adverse effect under certain circumstances and conditions. These factors can be divided into internal and external types. Internal factors are factors related to the individual itself, such as age, gender, genes, health status, psychological quality and so on. External factors are related to the environment of the individual, such as the social and economic environment, natural environment, political environment, cultural environment and so on.[20]

Dynamic Risk Analysis

Based on the collected multi-source data, risk portraits were developed for the function module of the risk assessment process att, t+2Δt, and + 2Δt according to the labelled content. These static images were then combined to create a dynamic risk portrait for epidemic risk assessment. The dynamic functional network diagram of the risk assessment module is shown in Figure 4. Using the FRAM model, the epidemic risk of an infectious disease was evaluated and described. The functional modules that output the risk assessment results were identified and labelled. Meanwhile, dynamic analysis of this functional module according to the risk evolution process was performed, and multi-dimensional evidence of multivariate data fusion was established. As shown in Figure 5 and Table 2, the failure function network diagram of the RIF barriers can reveal the impact on epidemic transmission.

In the study and judgment of a risk level, we can establish different probability models and logical relationships according to different characteristics and impact degrees of the epidemic risk. Then, a judgement can be made based on the evidence and theory. Specifically, probabilistic models and logical relationships based on data and evidence from different aspects can be developed, for example, models of the development trend of the epidemic, its transmission routes, and the effectiveness of prevention and control measures. In short, through the previous risk mapping step and the establishment and analysis of multi-dimensional evidence based on multivariate data fusion, a comprehensive risk assessment method for pandemics of infectious diseases can be achieved to provide a scientific basis and support for emergence response decision-making.

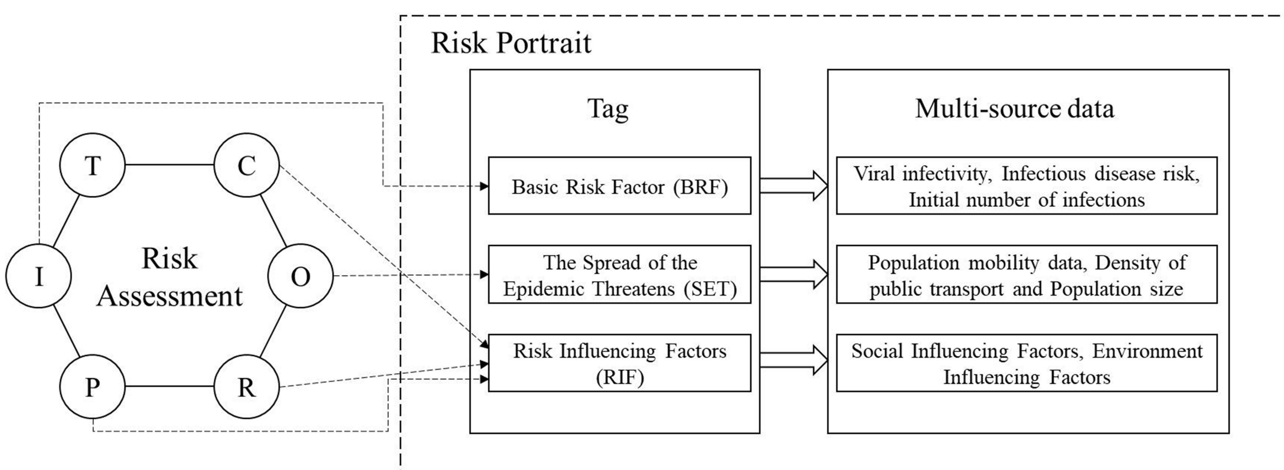

Figure 3 Static portrait model of function module label.

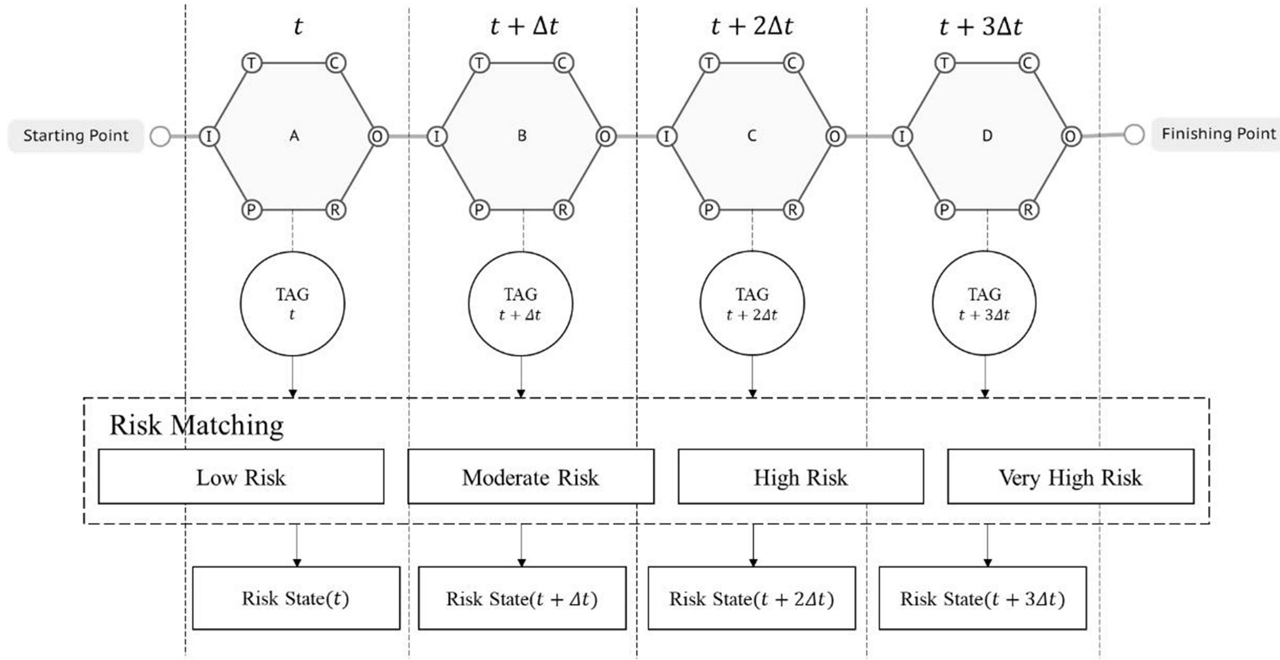

Figure 4 The dynamic functional network diagram of epidemic risk assessment.

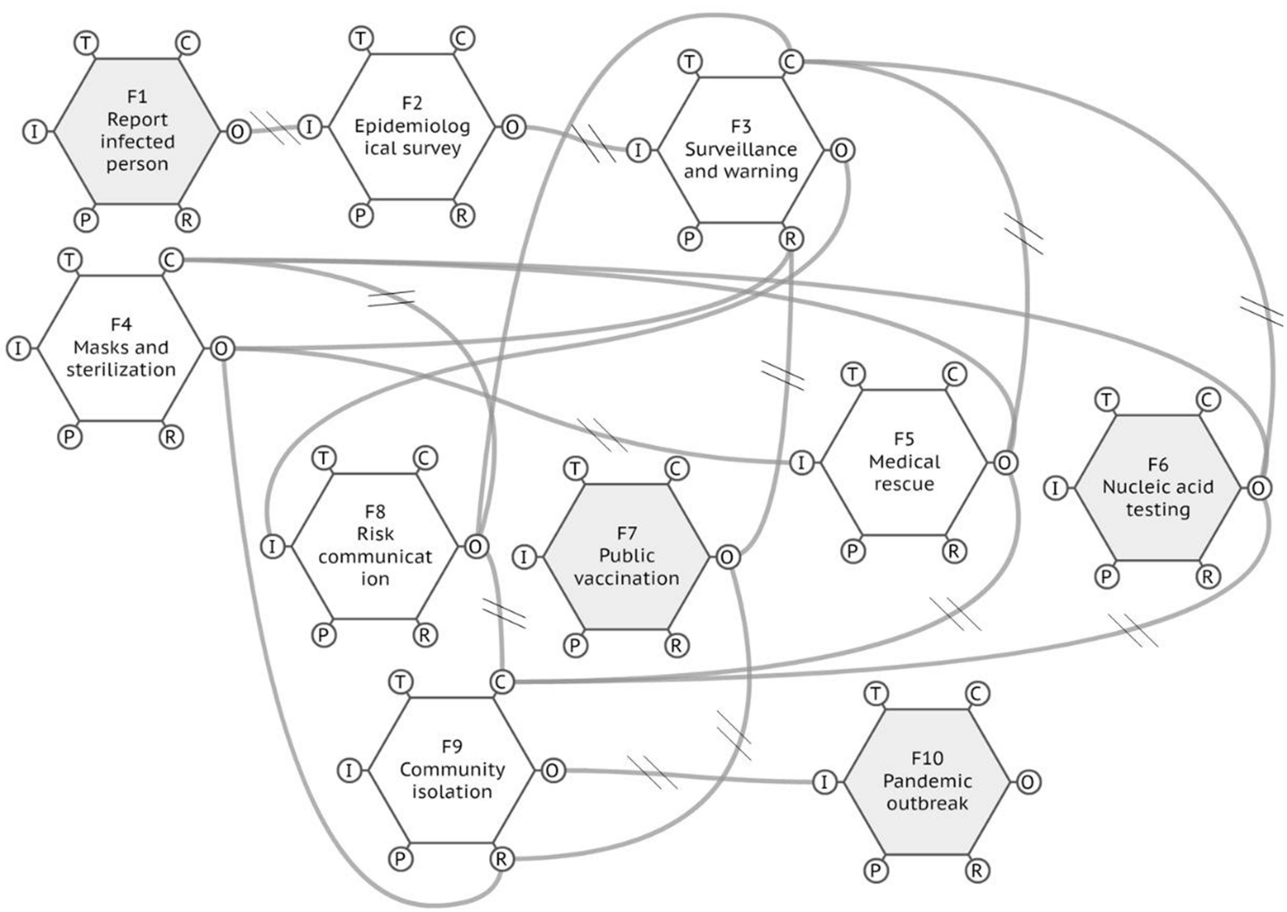

Figure 5 Failure function network diagram of RIF barriers impact on epidemic.

Table 2 Function and Tag Portrait List

Function Number	Function Description	Failure Function Link
F1	Find and report infected person	F1—F2
F2	Carry out epidemiological survey	F2—F3
F3	Risk surveillance and warning	F3—F5
F4	Masks and sterilization policies	F4—F5
F5	Medical rescue and bed supply	F5—F9
F6	Public nucleic acid testing	F6—F9, F6—F3
F7	Public vaccination	F7—F9, F7—F3
F8	Epidemic risk communication	F8—F9, F8—F4
F9	Community isolation policies	F9—F10
F10	Pandemic outbreak	

Application of FRAM to the Epidemic Risk Portrait

Case Selection

Wuhan is a national central city and is also an important transportation hub in the central region of China. According to data from the end of 2020, the population of Wuhan is about 15 million, and the average population density of Wuhan is 2334 people per square kilometre. The high population density increases the difficulty of preventing and controlling public health emergencies. In December 2019, a number of cases of pneumonia of unknown cause were successively identified in Wuhan. The virus was quickly identified as a new coronavirus, but the infectiousness and harm of the disease were not yet clear. After receiving the report on these infections, the State Council quickly dispatched a team of experts to assess the infections and make a judgement on the required response. On Jan 23, 2020, Wuhan was under "lockdown" control. Over the next two months, the outbreak was gradually contained. On Apr 8, the number of infected people in Wuhan was dynamically cleared to zero.

The evolution of the Wuhan epidemic were summarized in three stages, as shown in Figure 6. The determination of the timeline here takes into account not only the number of exposed infections, but also the corresponding policy introduction node for epidemic prevention and control. This would show how the risk of epidemic transmission may turn after controlling person-to-person contact.

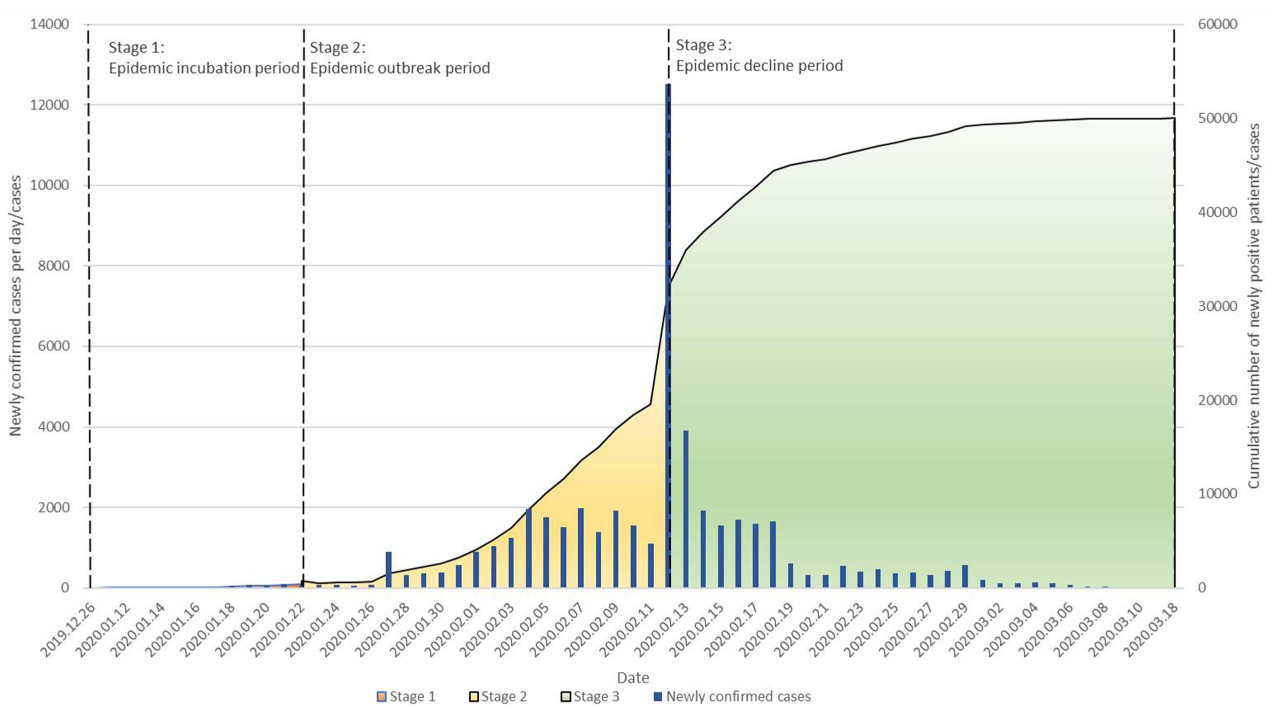

Figure 6 Phase evolution of the COVID-19 epidemic in Wuhan.

Stage 1: Epidemic incubation period (From 2019/12/26 to 2020/1/22). In this stage of risk uncertainty, the number of infectious disease appears was only sporadic in the single digits. Because it is difficult to find epidemiological correlation between accidental cases, it is difficult to use traditional prediction methods for risk assessment, and multi-source data fusion qualitative analysis method must be tried.

In the days following Dec 26, 2019, four patients with abnormal symptoms were admitted to the Wuhan Hospital. The information on these cases was provided to the Jianghan District CDC and the municipal government. On the 29th, the Wuhan city CDC instructed staff to carry out an epidemiological investigation. By reviewing the above timeline, it can be seen that there were not relevant warning signals at that time, they did not attract enough attention. On Dec 31, 2019, the national expert group arrived in Wuhan. On Jan 5, 2020, a new SARS-like coronavirus was detected in Shanghai based on samples from Wuhan patients. On Jan 6, 2020, the China CDC initiated a level II emergency response. However, from Jan 11 to 16, Wuhan's epidemic notification still did not clarify whether there was human-to-human transmission. Based on the above, it is clear that the epidemic had begun to spread, but due to the lack of effective epidemic risk analysis, the relevant department did not take timely risk control actions to respond epidemic and the public had not been warned. However, in the case of unprotected cities, the potential spread of infectious viruses has been rapidly progressing, and the risk of epidemics has not been fully recognized.

Stage 2: Epidemic outbreak period (From 2020/1/23 to 2020/2/12). In the afternoon of Jan 20, 2020, The authorities clearly announced that there was "human-to-human transmission" of the novel coronavirus pneumonia in Wuhan. On January 22, 2020, the Wuhan local government determined that the city was at a very high risk of the epidemic. The next day Hubei Province imposed strict controls on the outflow of people. At this day, Wuhan announced that the city would be "closed down" from 10 am on the same day. In the following weeks, the number of confirmed infections increased rapidly, peaking at 12,523 new infections on February 12. Due to the lack of control measures in the early stage, infected people were not completely screened out, thus, the "shut down" and other extraordinary measures did not achieve immediate results. This led to a shortage of hospital beds, medical equipment and medical staff, and patients waiting for diagnosis and admission.

Stage 3: Epidemic decline period (From 2020/2/13 to 2020/3/18). During this period, the cumulative number of infected people in the city continued to increase, but due to the implementation of the strict policy of prohibiting the movement of people, the transmission chain of the epidemic was effectively blocked, and the number of new daily infections continued to decline until it dropped to zero infections at the end of the period. The research model in this paper is mainly aimed at the risk analysis of the incubation period in the first stage of the epidemic, trying to capture the epidemic risk signs from the precursor information big data, so as to achieve early and rapid risk assessment and response.

Deriving Function Based on FRAM

In this study, a systematic model was used to analyse the transmission risk of COVID-19 in Wuhan. Three aspects of derived core functions and multi-source data were analysed for the risk portrait. The process of risk assessment was modelled using FRAM Model Visualizer Pro. According to the dynamic functional network diagram shown in Figure 4, the FRAM model was constructed to predict the pandemic risk change. The risk perception of an infectious disease epidemic refers to people's subjective judgments of the characteristics and severity of a specific risk. This is an important indicator of public psychological panic and infectious disease risk understanding. Everyone's understanding of a "risk" may be different; some people may think that the risk is objective, while some people may think that the risk is a subjective construction. The risk evolution of an infectious disease epidemic refers to the dynamic change process of

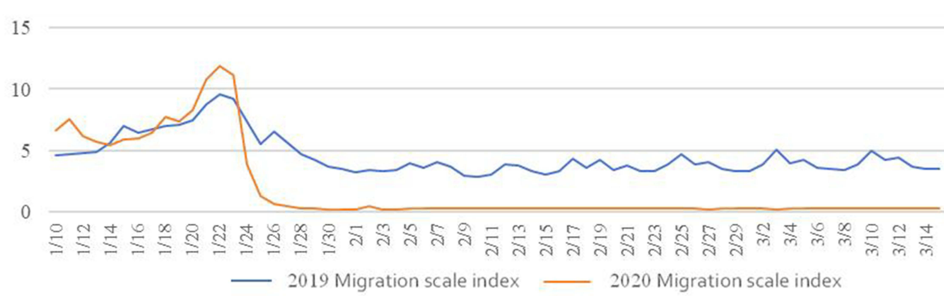

Figure 7 Wuhan population mobility data.

risk in time, space, target objects and other dimensions. In other words, in the formation and development process of the epidemic, this reflects the change laws and movement trajectory of risk from zero to existence, from small to large, from point to surface, under the action of various internal and external factors. The risk assessment of an infectious disease epidemic refers to the use of the theory and method of early risk assessment to capture the precursor signals of an infectious disease epidemic risk, identify and analyse the risk of the infectious disease, predict the possible epidemic risk level, and determine whether to issue corresponding early warning signals in the early stage of the emergence of infectious disease epidemic symptoms.

Multi-Source Data Selection

Population Mobility Data

Population Mobility Data (https://qianxi.baidu.com/#/): With the development of science and technology and the Internet, mobile devices have become universal equipment held by members of the population. The positioning data of mobile devices can effectively reflect the flow of the population. As the leading enterprise in domestic map navigation, Baidu launched the "Baidu Migration" data product, which can build a population migration data set for a city or province through people's usage of Baidu maps, positioning data, and mobile phone base station positioning. Since these data are not fully available, the "Emigration Scale Index" and "Immigration Scale Index" were chosen to represent the flow of the population. As shown in Figure 7, before the "lockdown", Wuhan's migration trend was very high compared with previous years. In reference to epidemic risk, maintaining such a high intensity of migration was a great challenge to national epidemic prevention and control. Therefore, Wuhan implemented a "lockdown" measure on February 23.

Internet Hot Search Data

Information on epidemic risk events often attracts the attention of the public and is reflected by hot search data on the Internet. Establishing a theoretical model of the association between Internet hot search data and the risk of new infectious diseases by taking Internet hot search data as the core and establishing labels for information sources, can help in the early detection of the risk of infectious diseases.

For example, Baidu Keyword Index (https://index.baidu.com/v2/index.html#/): In today's society, network information has become an important channel to obtain risk information. When the public and their relatives and friends feel unwell, the Internet is often the first point of consultation. Baidu Keyword Index can reflect the epidemic risk and distress faced by urban groups. It focuses directly on the keyword search volume. Take the keyword "mask" search in Wuhan, for example, as shown in Figure 8. Because wearing a mask is often an important measure to prevent respiratory infections.

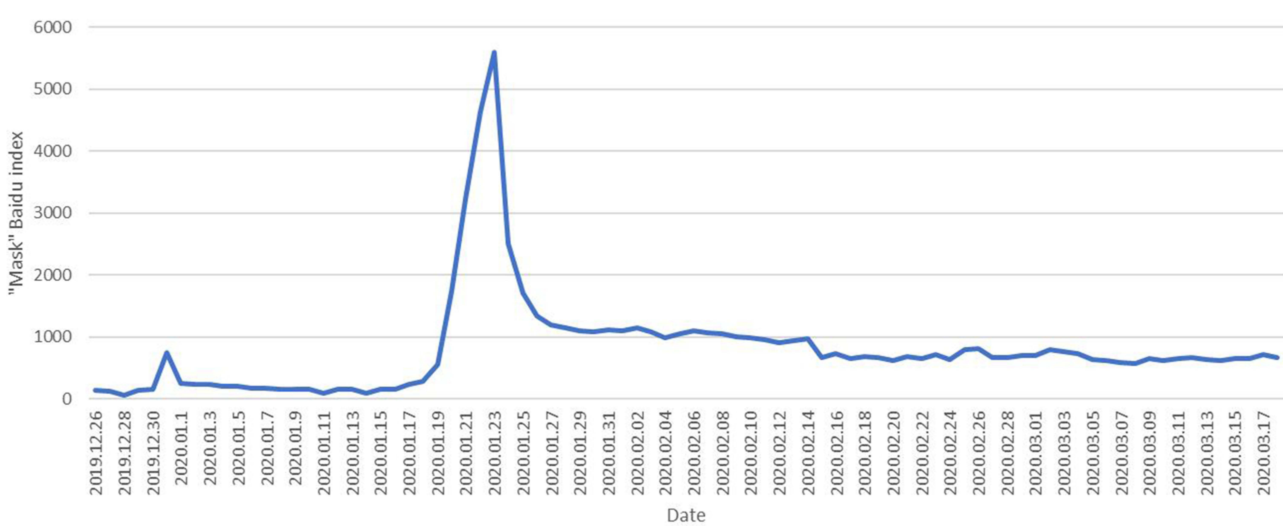

Figure 8 The Baidu search index of "mask" in Wuhan.

Density of Public Transport Network

The density of public transport in a city shows the potential for crowds to gather. The close contact of people increases the possibility of the epidemic spreading. Traffic Convenience (Baidu Map China Urban Transportation) showed that there are more than 750 public transport lines in Wuhan (including those not operated by Wuhan Public Transportation Group). According to the China Urban Transportation Report on Baidu Map 2020, the density of Wuhan's urban bus network is 3.311 km/km^2, and the density of the urban subway line network is 0.872 km/km^2.

Risk Portrait of Wuhan Pandemic Risk

Based on these multi-source data, together with the BRF, SET and RIF data in Table 3, the risk portrait was established, as shown in Figure 9. For example, the RIF data were used to help predict risk change, such as air temperature, community isolation policies and public epidemic prevention resources. This pandemic risk portrait in the different risk stages can be observed. An experienced expert team could then evaluate the epidemic risk level based on an inspection of the day's tag portrait. It could be found, although there was a low number of confirmed cases reported on January 22nd, other information, such as the mask and fever search indices and the density of the population and its mobility, provided a different picture. Thus, a very high risk of epidemic transmission would be predicted. This risk portrait assessment method may offer low confidence in the early application stage. Thus, in the assessment of acute public health events, a qualitative approach may be the only option, particularly early in the event when data are often limited or unavailable.[21]

Conclusion and Future Direction

Many public health events that pose a risk to human health, such as the COVID-19 pandemic, have been identified through the application of a systematic risk analysis process. This paper provides a rapid qualitative risk profiling tool based on multiple risk factors. This approach to epidemic risk analysis relies not only on accurate monitoring and collection of multiple risk information, but also on full and active risk communication among local governments, health experts and the public. Traditional risk assessment methods are facing great challenges in the early stage of epidemic risk prediction, Therefore, a new method of integrating BRF, SET and RIF multi-source data is necessary to be developed and gradually applied in practice, and constantly optimized. It is expected that with the accumulation of portrait features displayed by this method, more accurate risk portrait feature combinations will gradually be recognized and applied in the future risk monitoring and early warning of emerging infectious diseases. With the help of FRAM model, multivariate data of BRF, SET and RIF describing the full-dimensional portrait can be effectively integrated into the overall perception of epidemic risk. With the help of the FRAM dynamic functional network diagram, which reflects the failure of the RIF module, the risk of regional infectious disease outbreaks can be predicted and the current urban pandemic risk can be assessed. Although this paper provides an exploratory epidemic risk analysis method based on FRAM model, as a qualitative research method, It also requires a team of highly qualified evaluation experts who continuously accumulate experience. Learning from hazards and past epidemic cases could help to develop this risk profile assessment capability.

Table 3 Measurement Index Data Value of Wuhan

Tag	Measurement index	2020/1/16	2020/1/22	2020/2/12
BRF	Newly confirmed cases	4	62	12,523
	"Mask" search index	159	4637	910
	"Fever" search index	144	695	233
SET	Population size	15 million	15 million	15 million
	Density of ground bus network	3.311	3.311	—
	Density of subway network	0.872	0.872	—
	Migration scale index	5.852	12.264	0.002
RIF	Maximum air temperature	3	13	7
	Community isolation policies	No	Actuation point	Yes
	Public epidemic prevention resources	Short of	Tense	Abundant

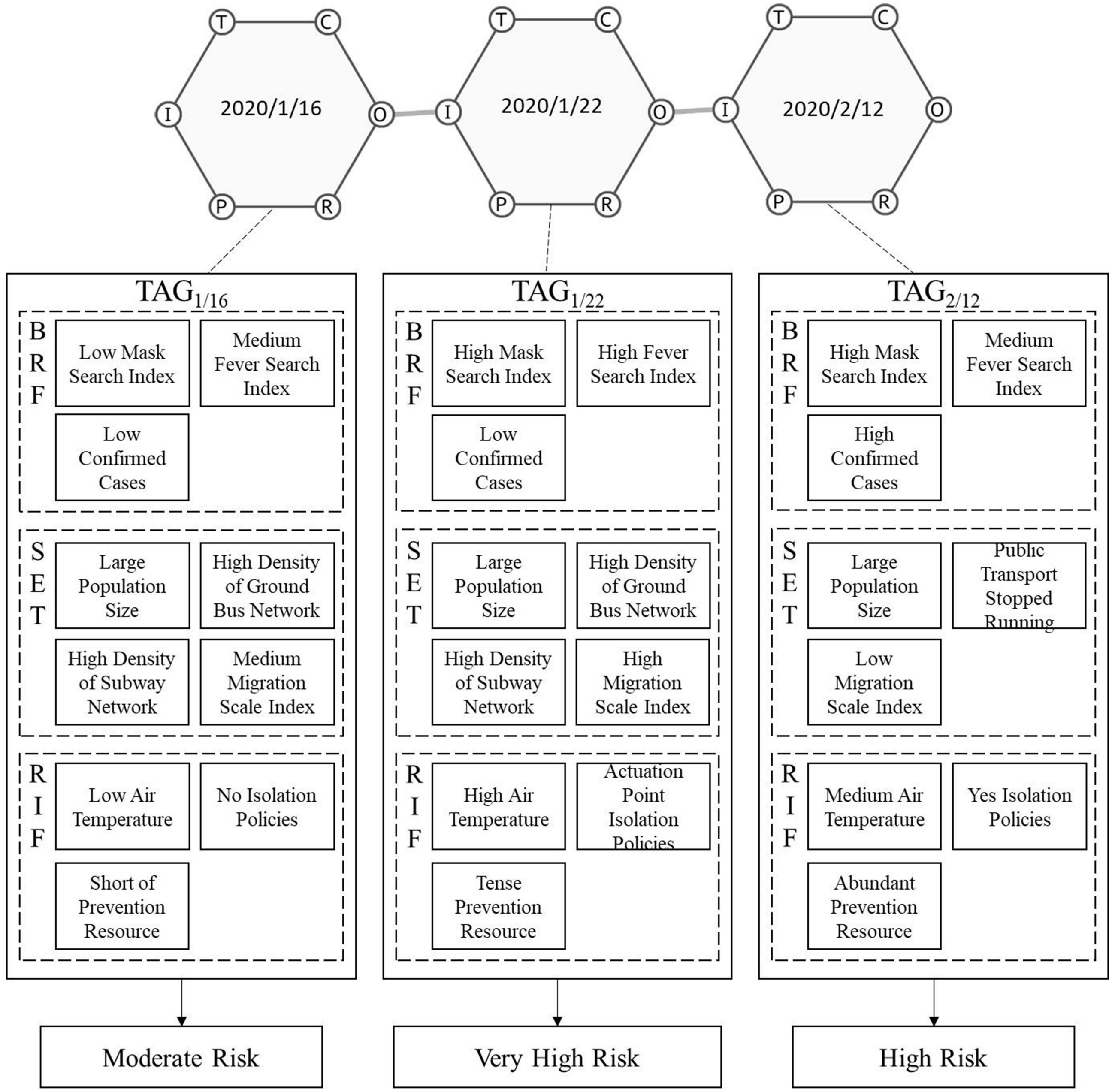

Figure 9 The risk portrait of Wuhan Pandemic in 2020.

Whether the model can be applied effectively depends on the reform and effective operation of the institutional mechanism of risk management of infectious diseases. For example, in China, a regular monthly risk assessment system for infectious diseases has been established during non-epidemic periods, and this risk assessment without ascertaining medical patients is expected to play a positive role in qualitative risk assessment methods based on FRAM model and multi-source big data. At the same time, in order to ensure the accuracy and timeliness of epidemic risk assessment, the multi-point triggered infectious disease monitoring and early warning system currently being built across China will provide reliable information sources for risk assessment, thus forming a resilient public health emergency response system.

Abbreviations

FRAM, Functional Resonance Analysis Method; CDC, Centers for Disease Control and Prevention; BRF, Basic Risk Factors; SET, the Spread of Epidemic Threats; RIF, Risk Influencing Factors; COPD, Chronic Obstructive Pulmonary Disease; OHS, health and safety; STPA, system theory process analysis; VSM, Value Stream Map.

Data Sharing Statement

The original contributions presented in the study are publicly available. The case data information is publicly available on the Internet. It can also be available from the corresponding author on reasonable request.

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Disclosure

The authors report no conflicts of interest in this work.

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