COVID

Review

A Review of Environmental Factors for an Ontology-Based Risk Analysis for Pandemic Spread

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Abstract: Contact tracing is a method used to control the spread of a pandemic. The objectives of this research are to conduct an empirical review and content analysis to identify the environmental factors causing the spread of the pandemic and to propose an ontology-based big data architecture to collect these factors for prediction. No research studies these factors as a whole in pandemic prediction. The research method used was an empirical study and content analysis. The keywords contact tracking, pandemic spread, fear, hygiene measures, government policy, prevention programs, pandemic programs, information disclosure, pandemic economics, and COVID-19 were used to archive studies on the pandemic spread from 2019 to 2022 in the EBSCOHost databases (e.g., Medline, ERIC, Library Information Science & Technology, etc.). The results showed that only 84 of the 588 archived studies were relevant. The risk perception of the pandemic (n = 14), hygiene behavior (n = 7), culture (n = 12), and attitudes of government policies on pandemic prevention (n = 25), education programs (n = 2), business restrictions (n = 2), technology infrastructure, and multimedia usage (n = 24) were the major environmental factors influencing public behavior of pandemic prevention. An ontology-based big data architecture is proposed to collect these factors for building the spread prediction model. The new method overcomes the limitation of traditional pandemic prediction model such as Susceptible-Exposed-Infected-Recovered (SEIR) that only uses time series to predict epidemic trend. The big data architecture allows multi-dimension data and modern AI methods to be used to train the contagion scenarios for spread prediction. It helps policymakers to plan pandemic prevention programs.

Keywords: COVID-19; epidemiology; health policy; health systems; review

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Citation: Cheung, L.; Lau, A.S.M.; Lam, K.F.; Ng, P.Y. A Review of Environmental Factors for an Ontology-Based Risk Analysis for Pandemic Spread. *COVID* **2024**, *4*, 466–480. https://doi.org/10.3390/covid4040031

Academic Editor: Somenath Chakraborty

Received: 3 March 2024
Revised: 28 March 2024
Accepted: 31 March 2024
Published: 11 April 2024

KEY MESSAGES

WHAT IS ALREADY KNOWN ON THIS TOPIC

- The Susceptible-Exposed-Infected-Recovered (SEIR) models are widely used to predict possible contagion scenarios. It uses individuals' contagion statuses, such as not yet infected, incubation period, confirmed cases, and recovered or dead cases to build the pandemic spread model.
- Pandemic spreading, however, depends on how the environmental factors influencing human behaviors of pandemic prevention. It is not a linear problem but is a multi-dimensional and non-linear problem.

WHAT THIS STUDY ADDS

- This research, therefore, identified the major environmental factors from literatures, including fear of the spread of the pandemic, attitudes toward hygiene practices, community culture, government policies on pandemic prevention, economic activity restrictions, pandemic education, multimedia, and technologies uses for information dissemination and disclosure, resulting in an increase in the spread of the pandemic.

- The design of ontology-based big data architecture uses ontologies, sentiment analyses, a clustered 3D CNN model, and a clustered GCN model to model the environmental factors into different dimensions and uses the 3D-CNN/GCN architecture to model the contagion scenarios for spread prediction.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE, OR POLICY

- The conceptual design of the big data information architecture allows researchers to continue our work to conduct the sentiment analyses of the government policies and use the 3D-CNN/GCN architecture to model the complex contagion scenarios for predicting individual or community's pandemic spreading risk that no researchers have done before.

1. Introduction

Coronavirus disease 2019 (COVID-19) has spread continuously from 2019 to 2022 and has had a significant impact on our health, economy, and society. The contact-tracking method is an effective way to monitor the potential spread in the community and can reduce the rate of pandemic spread [1–3]. It collects a contact person's demographics, contact location, time, frequency, and duration to predict a pandemic outbreak in the community [4]. Online and offline questionnaires, barcodes, mobile phones, wireless sensors, Wi-Fi, Bluetooth, RFID, global positioning systems, and QR codes are commonly used devices [5–7] to collect individuals' daily activities to monitor the potential pandemic spreading routes in the community so that policymakers can make an instant response to the pandemic outbreak and develop timely pandemic prevention strategies.

However, traditional contact-tracking methods only capture the contacted person's daily activity for analysis and not environmental factors. Kong et al. (2021) found that demographic, economic, environmental, hygiene, and social networks were major factors that accelerated the spread of the pandemic [8]. Therefore, the aim of this research was to review the potential environmental factors that could cause pandemic outbreaks and propose an ontology-based big data architecture to capture the environmental factors in the contact network for predicting pandemic outbreak risk. Environmental factors are reviewed in the following sections. Ontology and big data architectures are discussed to capture and embed these factors into the contact-tracing network. Finally, the conceptual framework of an ontology-based big data architecture is presented.

2. Literature Review

To successfully control the spread of a pandemic, a good understanding of an individual's risk perception [9], hygiene measures, intentional behavior, and cultural behavior is essential. Government leadership in pandemic prevention programs, public education, technology use, information disclosure, and economic stability control planning are critical for successful pandemic control [10]. Zhang et al. (2020, 2021) [11,12] found that the government, which established policies on travel restrictions, patient flow control, mandatory vaccination, social distancing, community containment, isolation, and quarantine, effectively controlled the spread of COVID-19. Individuals and communities well-educated in pandemic risk and adopting pandemic prevention methods, including wearing masks, washing hands, COVID-19 self-testing, hygiene practices, vaccination, and self-quarantine, have significantly prevented COVID-19 transmission to others. People in some countries, however, are reluctant to take action for pandemic prevention because of their culture and religious beliefs resulting in higher COVID-19 transmission [7]. The cultural factors of collectivism, information-seeking behavior, symbolism of masks, and previous pandemic experience are the major barriers to pandemic prevention behavior [13]. Ting et al. (2021) found that different ethno-religious groups had different religious beliefs and cultural behaviors that could affect the practices of hygiene measures and prevention methods [14]. Rivas et al. (2021) found that social media played an important role in the diffusion of information and changes in cultural behavior during the COVID-19 pandemic [15]. Social media is an effective channel for promoting pandemic-preventive behaviors and educating the public on pandemic-prevention procedures.

Some emerging technologies such as social contact monitoring systems, COVID-19 reporting systems, and temperature measurement devices in public areas are effective methods for monitoring and controlling the spread of pandemics [16,17]. Studies have indicated that the extensive use of digital technology and government strategies can reduce the spread rate of the pandemic. The policies of closed cities, travel bans and quarantines, economic activity restrictions, and COVID-19 vaccination requirements have provided evidence to successfully control the spread of COVID-19 [18]. Only some business restriction policies, such as a temporary breaking of the global supply chain, production line shutdown, reduction in import and export trading activities, decrease in demand and supply of goods, and gross domestic product (GDP), caused negative impacts and damaged the local economy. Therefore, a government with good planning for the suspension of economic activities and a recovery plan can reduce these impacts and recover the economy. Virtual meeting tools, work-from-home arrangements, financial assistance to small businesses and enterprises, and social security subsidiaries are some examples of effective solutions for virtually maintaining business activities and economic growth during closed cities during the COVID-19 pandemic.

To be more systematic in studying how these environmental factors impact the spread of the pandemic, this research conducted an empirical study and content analysis to identify the environmental factors that could cause the pandemic outbreak and to embed these factors in developing an ontology-based big data architecture for pandemic outbreak prediction in the community.

3. Research Methods

This research used an empirical study and content analysis methods to determine the environmental factors. A literature review was conducted and content analysis was performed to identify the environmental factors from articles that caused the pandemic outbreak. Frequency counting of the articles was used to summarize the relevant environmental factors. Grounded theory of information coding, grouping and classification, and theme generation was used to analyze the environmental factors. Literature and self-exploration were used to explain the findings. The identified environmental factors were used to build a conceptual framework of the ontology-based pandemic spreading risk analysis. The processes of extraction, selection, and analysis of studies are summarized as below.

Extraction Process: The environmental factors of pandemic spread may appear in journals of medicine, health informatics, health policy, technology, the environment, and biological science. The EBSCOHost database integrates other databases, such as Medline, ERIC, Library, Information Science and Technology Abstracts, that contain journals related to medicine, health informatics, science, healthcare, and technology. It was selected to archive related studies during the pandemic period (i.e., 2019–2022). The keywords contact tracking, pandemic spreading, fear, hygiene measures, government policy, prevention program, pandemic program, information disclosure, pandemic economic restriction, and COVID-19 were used to archive the studies relating to pandemic outbreak, pandemic prevention, and government policies.

Selection Process: After initially reviewing the relevant literature, the following inclusion criteria and exclusion criteria were applied. The inclusion criteria were as follows: (1) studies published during the pandemic period (2019–2022); (2) all empirical studies, review articles, and case studies in peer-reviewed journals; (3) studies examining all types of government policies, pandemic prevention programs, education programs, technologies for pandemic disclosure and dissemination, and analyses of environmental psychological, and human behavioral factors influencing different national policies on pandemic spreading. The exclusion criteria were as follows: (1) studies covering COVID-19 in general and not related to the factors influencing the pandemic spreading and (2) studies that focused on personal health, pharmacological intervention, and pathological evidence.

Analysis Method: Grounded theory was applied to information coding, grouping and classification, and theme generation to analyze the environmental factors. Firstly, the substantive environmental factors causing pandemic spreading, such as fear, hygiene, culture, and government policies were identified. Second, the concepts and categories of environmental factors were analyzed. For example, the concepts of fear include subjective distress, behavioral avoidance, and physiological arousal. The categories of fear are fear of ill health, fear of death, and fear of behavioral change. Third, a content analysis was performed using open and selective coding. The open codes were identified from the articles by marking the segments of the sentences using symbols, descriptive words, or unique identifying names. The codes were selected by comparing the concepts and categories and similar selected codes were grouped together. Fourth, theoretical coding was done by constantly comparing and establishing connections between the concepts and categories, sorting and reviewing the categories, and asking questions to determine any new category. Fifth, the links and the relations between the categories and the environmental factors were identified to determine new environmental factors. Lastly, the number of articles on environmental factors was recorded.

Explanation of Findings: Additional papers were used to explain the causes of the findings. A self-exploratory method was used; specifically, it involved asking what the constructs of the environmental factors were, why these constructs create environmental risks for pandemic spread, and how these environmental risks were reduced. This method revealed the causes of the identified environmental factors and was used to derive insights from the analysis.

4. Results

The results of the content analysis are summarized in Table 1. A total of 588 studies from 2019 to 2022 were archived, and only 84 studies were relevant to pandemic outbreak topics. By analyzing the content, we found that fear of the spread of the pandemic, hygiene practices, community culture, attitudes toward government policies on pandemic prevention, pandemic education, economic and business activity restrictions, technology, and multimedia for information dissemination and disclosure were the major environmental factors resulting in an increase in the spread of the pandemic.

Table 1. Summary of the review results.

Keywords Search with COVID-19	Relevant/Returned Studies	Environmental Factors	References
Fear, anxiety, worry	14/127	Fear of the spread of pandemic	[9,15,19–30]
Hygiene practice	5/7	Intentional behaviors of hygiene practices	[31–35]
Pandemic prevention	12/96	Cultural behaviors of pandemic prevention	[14,36–45]
Government policy, pandemic policy	25/220	Government policies on pandemic prevention	[11,12,46–68]
Pandemic education program	2/31	Attitudes of pandemic education program	[69,70]
Pandemic economic, business restriction	2/16	Attitudes of economic and business restrictions	[71,72]
Contact-tracking technology, Multimedia, channel, information dissemination	24/91	Attitudes of technology infrastructure and multimedia for information dissemination and disclosure	[2,18,73–94]

5. Discussion

The identified environmental factors affecting the spread of the pandemic can be explained as follows.

5.1. Fear of the Pandemic Spreading

The more deaths and confirmed cases of COVID-19, the more people would perceive an increase in the risk of getting sick and would start to comply with pandemic prevention measures, such as washing hands, social distancing, and quarantine [95] to mitigate the spread of the pandemic. However, some people may not be inclined to comply with pandemic prevention measures for social and economic reasons, prefer to continue their normal social activities and work for income, or may not be afraid of the pandemic. This explains why several waves of the COVID-19 pandemic occurred between 2019 and 2022. Decomposed planned theory explains that one's actual behavior is influenced by intentional behavior, and peer influence is one of the determinants of one's intentional behavior [96]. The more the discussion on fear of the pandemic, the more the actual behavior of pandemic prevention would take [97]. Fear of COVID-19 was a determinant of the spread of the pandemic. Since social media can affect one's mood and could cause the symptoms of depression, anxiety, and stress of a person, it is a good indicator for measuring one's intention [98]. Social media data on fear of the pandemic is recommended to be collected to measure how social media influences an individual, community, and nation's pandemic prevention intention for predicting pandemic spreading risk.

5.2. Hygiene Practices and Pandemic Transmission

The droplet and aerosol transmission theory explains how COVID-19 can spread widely in the community [99]. Viruses are primarily transmitted between individuals via respiratory droplets and contact. Physical contact with confirmed or suspected COVID-19 patients, gathering activities, touching mouth and nose, not washing hands, and not wearing masks are the major media for transmission [100]. So, hygiene behaviors, such as hand washing and mouth covering, are essential for mitigating pandemic transmission and are one of the determinants of the pandemic spreading. In the decomposed planned behavioral model [101,102], actual human behavior is influenced by intentional behavior. This intentional behavior is determined by peer influence, government influence, resources, and technology-facilitating conditions. Attitude toward hygiene practices is a determinant of pandemic transmission. By using social media data from hygiene discussions on pandemic prevention, the attitudes toward hygiene practices of an individual, community, or nation can be measured and used to predict the risk of pandemic spread.

5.3. Cultural Behavior of Pandemic Prevention

During the COVID-19 pandemic, some countries had looser rules to control their behaviors in pandemic prevention. In contrast, some countries had stricter rules and regulations for individuals. Cultural differences resulted in different levels of the pandemic spreading [10,13]. A country with a tighter culture can migrate significantly more during a pandemic [103,104]. Therefore, culture is a determinant of the success of government policies to prevent pandemic spreading. The adoption of the policy depends on how it being created, developed, and transmitted by a group of people and the compatibility of one's behaviors to execute the policy. In Chen's study, culture was constructed by social behavior, individuals' knowledge, beliefs, norms, values, traditions, habits, abilities, and laws [104]. Thus, social media data is recommended to be used to analyze an individual, community, and nation's common beliefs, attitudes, feelings, ideas, norms, and values on government pandemic prevention policies for predicting pandemic spreading risk.

5.4. Attitude of Government Policies on Pandemic Prevention

Various public health policies, including wearing masks, social distancing, home quarantine, travel restrictions, stay-at-home orders, lockdown, business activity restrictions, and closure of businesses and schools, have been adopted by different countries to prevent a pandemic outbreak. However, the adoption of pandemic prevention policies highly depends on individuals' intentional behaviors [105]. The determinants of the intentional adoption behavior were classified into perceived usefulness; perceived ease of use;

resource- and technology-facilitating conditions, and the influence of peers, companies, and governments [101,102]. Wollast et al. (2021) found that the major determinants of an individual's compliance with pandemic prevention policies include an understanding of the usefulness of pandemic prevention, perceived ease of use of prevention methods, economic status, availability of education resources, technology infrastructure, and media channels for information dissemination [106]. So, social media is recommended to be used to determine the public's sentiments toward government policies on pandemic prevention, economic activity restrictions, education programs, telecommunications, and multimedia infrastructure for information dissemination. Sentiments can be used to predict individuals' intentional behaviors to adopt prevention policies. The government policies are further discussed below.

5.5. Economic and Business Restrictions

Economic and business restrictions have negatively affected the global business economy. The shutdown of economic activities resulted in a decrease in global GDP of more than USD 400 billion from the pre-pandemic level and economic loss of business firms, product manufacturers, services, and the tourism industry [107]. Sizable employee layoffs; rising unemployment rates; a reduction in family income levels; an increase in individual, household, and business loans; economic hardships; the economic recession have created many societal problems [107]. Consequently, individuals and businesses in some countries refused to comply with the policy of business activity shutdowns and conducted street protests. It is important to understand the public and business attitudes and opinions toward government policies before they are launched. Therefore, social media can be used to measure the public's attitude toward government policies regarding economic and business restrictions.

5.6. Pandemic Prevention Education Programs

Education programs on pandemic prevention can change risk perceptions and hygiene behaviors of individuals. Public campaigns, workshops, media, and education programs can raise public awareness of pandemic prevention and educate people about appropriate hygiene behaviors. Consequently, it can prevent the transmission of pathogens and diseases between individuals and communities. Kundu et al. (2021) found that online health education programs focusing on young people, housewives, and people with less education could improve attitudes toward COVID-19 pandemic prevention in the long run. Therefore, social media is recommended to be used to listen to the public's attitudes toward governmental pandemic education programs. Sentiments can be used to predict the risk of spreading a pandemic among individuals, communities, or nations [108].

5.7. Technology Infrastructure and Multimedia for Information Disclosure

Finally, several pandemic prevention resources, such as technology infrastructure and multimedia channels, are essential for information disclosure. According to the theory of rumor transmission [109], faster information transmission can reduce the spread of rumors. Good telecommunication and information infrastructure in a country can enable faster delivery of correct pandemic information to the public [110]. The number of information disclosure channels and technologies used are some of the determinants of the success of government policies to mitigate pandemic spreading. Therefore, social media is recommended to be used to listen to the public's attitudes toward the governmental multimedia and technologies used for pandemic information dissemination and disclosure. Sentiments can be used to predict the risk of spreading a pandemic among individuals, communities, or nations.

6. Recommendations

To collect these environmental factors for predicting pandemic outbreak risk, the measurement metrics, metric data collection, and calculation methods for future work are summarized in Table 2.

Table 2. Methods for quantifying the environmental factors of the spread of pandemic.

Environmental Factors	Measurement Metrics or Experiments for Future Work
Fear of the pandemic spreading	Fear index is a measurement metric to measure the risk perception on pandemic spread of individuals. The public sentiments on the fear of the pandemic spread (e.g., stress, anxiety, etc.) from social media are calculated.
Intentional behaviors of hygiene practices	Hygiene index is a measurement metric to measure the attitudes of hygiene practices of individuals (e.g., handwash, wearing mask, social distancing, contact tracking, decontamination, etc.) for pandemic prevention. The public sentiment scores on hygiene practices are calculated from social media.
Cultural behaviors of pandemic prevention	Culture index is a measurement metric to measure the cultural attitudes on pandemic prevention (e.g., handwash, wearing masks, social distancing, contact tracking, decontamination, etc.). The public sentiment score of pandemic prevention of different races or religions from social media are calculated.
Attitudes of government policies on pandemic prevention	Policy index is a measurement metric to measure the attitudes of government policies on pandemic prevention (including pandemic prevention, education programs, economic and business activity restrictions, technology and multimedia infrastructure). The public sentiment score of government policies on pandemic prevention are calculated from social media.
Attitudes of pandemic education program	It is a sub-score of policy index. This measures the attitudes of the governmental pandemic education programs (e.g., procedures of wearing masks, washing hands, and COVID-19 testing). The public sentiment score on governmental pandemic education programs from social media are calculated.
Attitudes of economic and business restrictions	It is a sub-score of policy index. This measures the attitudes of the economic and business restriction policies (e.g., lockdown cities, travel ban and quarantine, and COVID-19 vaccination requirement of visitors). The public sentiment score on economic and business restriction policies from social media are calculated.
Attitudes of technology infrastructure and multimedia for information dissemination and disclosure	It is a sub-score of policy index. This measures the attitudes of the technology infrastructure for information dissemination (e.g., social monitoring app, COVID-19 reporting system, and temperature measurement equipment in public places) and the multimedia for information disclosure (e.g., news, social media, and government web pages). The public sentiment score on technology infrastructure and multimedia for pandemic information dissemination from social media are calculated.

An information architecture for an ontology-based risk analysis for pandemic spread was proposed (Figure 1) to integrate these environmental factors into the contact-tracking analysis, and the key points were summarized below.

- First, contact-tracing data, social media data, pandemic prevention methods, government policies for pandemic prevention, educational programs, business activity restrictions, multimedia, and technology infrastructure were collected. The contact-tracing data were modeled using an ontology. The ontology defines the attributes and behaviors of entries [111,112].
- Second, the discussion topics on social media were classified into pandemic fear, hygiene measures, cultural practices, prevention policy, education programs, business activity restriction, multimedia disclosure, and technology infrastructure for sentiment analysis. Commonly used topic classification methods include Naïve Bayes, support vector machine model, and linear discriminant analysis.
- The keywords of the posts for each topic were extracted to measure the pandemic indices of fear, hygiene, culture, and policy in the next step [79,113]. Natural language

processing, word frequency count, term frequency-inverse document frequency [114], and n-gram [115] are commonly used text analysis methods for keyword extraction.

- Categorical and dimensional methods are the two major sentiment-analysis methods [116,117]. The categorical method classifies sentiments into different fear descriptors, such as sadness, nervousness, and worry [116,117]. The dimensional method classifies sentiments into positive and negative affectivity [117–119]. The extracted keywords and phrases were mapped to the vocabularies of categorical and dimensional databases. The classified sentiments were counted and used to calculate fear, hygiene, culture, and policy indices. Some artificial intelligence methods such as the support vector machine model, word2vec, TextCNN, and 2D CNN methods can be used together with sentiment counts to predict sentiments [120–124].
- After the sentiments were analyzed, a clustered ontology model was constructed to capture the four indices' values per demographic group to predict the individuals' pandemic spreading risk based on their demographic information. The contact-tracing information of contact activity, time, location, duration, and contact person can be used to predict the network-driven individual pandemic spread risk based on the connected nodes in the network. The community outbreak risk in the contact network was calculated. The 3D CNN network analysis model and graph convolutional network [125] can be used to train and predict individual risks and network-driven individual risks using the COVID-19 test history and the COVID-19 test result, respectively. Policymakers can use this information to plan pandemic prevention programs.

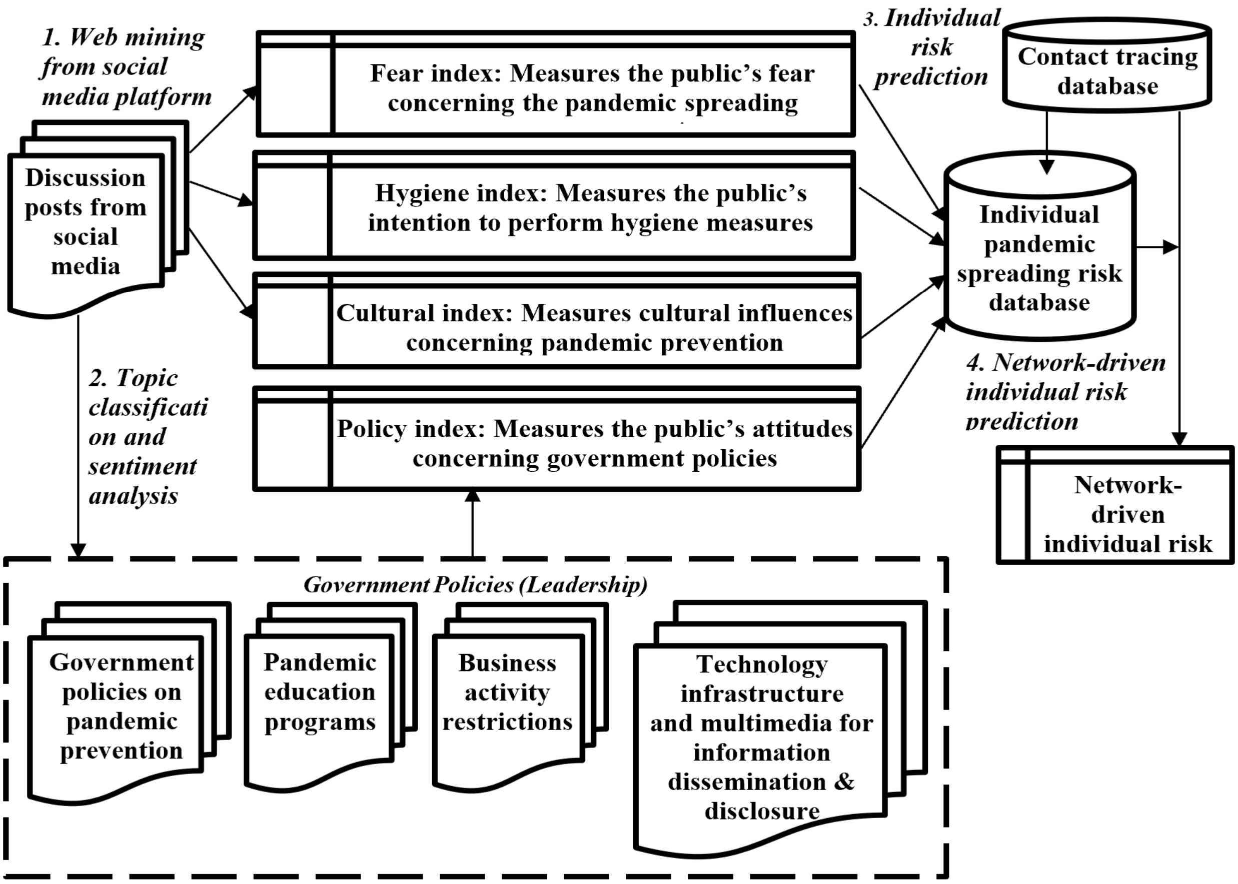

Figure 1. Information architecture for the pandemic spreading risk prediction.

A high-level design of the ontology (Figure 2) was presented to demonstrate how ontology to be used to model the relationships between the found factors for data visualization.

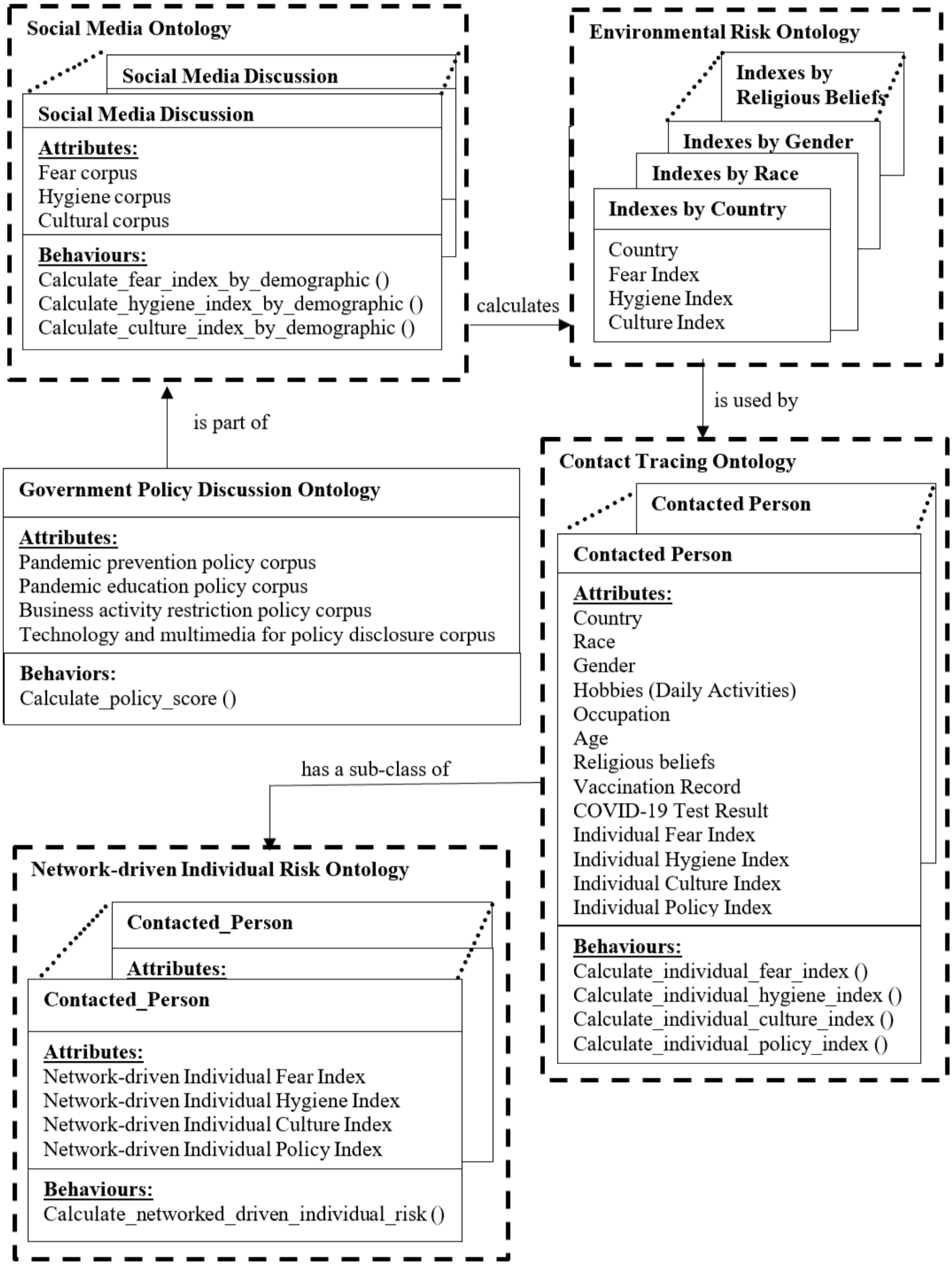

Figure 2. A high-level design of the ontology for contact tracking.

7. Conclusions and Future Work

In conclusion, the traditional pandemic outbreak prediction model considers only the contact information of individuals when predicting a pandemic outbreak. It does not consider how environmental factors influence the actual behavior of individuals in pandemic prevention, resulting in different levels of pandemic outbreak risk. This research used an empirical study and a content analysis method to identify the key environmental factors and proposed ontology, text analysis, sentiment analysis, and network analysis methods for quantifying the pandemic environmental factors and embedding them into contact-tracing information to predict the pandemic outbreak risk. It overcomes the limitation of the SEIR model that only uses time series to predict pandemic spreading risk. The big data architecture allows us to model the complicated contagion scenarios for spread prediction. In future work, OWL/XML and Jena will be used to model the factors of pandemic spread and the spreading processes of the ontology. A sentiment analysis of pandemic prevention and attitudes expressed on social media will also be conducted. The cluster-based ontologies and 3D-CNN/GCN models for pandemic outbreak prediction will be implemented. Since the environmental factors were found in the literature, a correlation analysis of these environmental factors and the increase in pandemic spreading risk will be studied.

Author Contributions: Conceptualization, A.S.M.L.; methodology, A.S.M.L., K.F.L. and L.C.; software, A.S.M.L. and L.C. validation, K.F.L. and P.Y.N.; formal analysis, L.C.; investigation, A.S.M.L., P.Y.N. and K.F.L.; data curation, L.C.; writing—original draft preparation, L.C. and A.S.M.L.; writing—review and editing, A.S.M.L., K.F.L. and P.Y.N.; visualization, A.S.M.L.; supervision, A.S.M.L., K.F.L. and P.Y.N.; project administration, A.S.M.L. All authors have read and agreed to the published version of the manuscript.

Funding: There is no funding source for this research.

Institutional Review Board Statement: There is no ethical approval is needed.

Data Availability Statement: The data source is from EBSCOhost Database.

Acknowledgments: We would like to acknowledge the HKU SAAS Data Science Lab to provide the research collaboration environment to the authors.

Conflicts of Interest: There is no conflict of interest in this research study.

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