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Identification and prioritization of safety barriers to prevent and reduce the infection of the COVID-19 using fuzzy DEMATEL-BAYESIAN modeling: lesson learned

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Authors
Omran Ahmadi, *PhD*[1*]

[1] Department of Occupational Health Engineering, Faculty of Medical Sciences, Tarbiat Modares University, Tehran, Iran.

**** Correspondence***
Department of Occupational Health Engineering, Faculty of Medical Sciences, Tarbiat Modares University, Tehran, Iran.
E-mail: O.ahmadi@modares.ac.ir

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ABSTRACT

Background: The COVID-19 pandemic resulted in widespread outbreaks and a significant increase in mortality among both the general population and the workforce over a span of two years. This study aimed to identify and prioritize measures for preventing and reducing the incidence of COVID-19 through the application of fuzzy DEMATEL-Bayesian modeling.

Materials & Methods: In the first phase, key factors in the prevention and reduction of COVID-19, as identified in past studies, were reviewed and extracted. In the second phase, the cause-and-effect relationships of these factors in the prevention and control of COVID-19 were established using the fuzzy DEMATEL method. In the third phase, the identified factors were integrated into a Bayesian network based on the findings from the previous phase.

Findings: The analysis identified seven critical factors in the prevention and control of COVID-19: personal protective equipment, social distancing, technology, training, lessons learned, geographical factors, and attention to sensitive age groups. The results indicated that the prevention and reduction node of COVID-19 was most sensitive to social distancing, more so than any other factor.

Conclusion: Based on the sensitivity analysis of the model, the first priority in decision-making for preventing and reducing COVID-19 should be focused on social distancing. The Bayesian network model developed in this study can effectively assist in macro-level decision-making by prioritizing the measures necessary to control and reduce the spread of the COVID-19.

Keywords: COVID-19, prevention and control, Public Health

CITATION LINKS

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Introduction

Advancements in technology have increased human vulnerability to systemic risks, such as the spread of diseases like COVID-19. Effective safety measures and barriers are crucial in mitigating these risks and preventing disease transmission. Safety involves implementing measures to reduce risks and mitigate hazards effectively. In the context of COVID-19, safety barriers act as critical defenses to break the chain of transmission and limit the spread of the disease. From a systemic safety perspective, the COVID-19 pandemic represented an issue with a medical surface but a systemic core. Thus, leaving the problem solely to the healthcare system is insufficient for resolution. Addressing additional influential factors in preventing and controlling COVID-19 can establish robust barriers to curbing the spread of the virus and mitigating its damage [1]. Effective safety measures for COVID-19 prevention encompass multiple protective layers, particularly those aimed at reducing the incidence of infection before reaching diagnostic and treatment stages. Each layer can integrate engineering, managerial, and individual interventions to enhance its performance. These measures collectively disrupt the virus transmission chain, significantly limiting the number of cases reaching the healthcare system. Consequently, patients who do require diagnosis and treatment can access improved medical services.

Engineering solutions, especially those leveraging artificial intelligence and information technology, play a vital role in identifying behavioral patterns of humans and the virus, enabling proactive actions through big data analysis. However, managerial and individual controls are often easier to implement and more accessible. Responsibility for identifying and applying control measures within each layer lies with the organizations operating in those respective layers. In a dynamic system, these layers undergo continuous evaluation to assess the effectiveness of their interventions and to adapt through iterative decision-making processes, such as the Deming cycle [2]. From an occupational health and safety perspective, identifying and prioritizing prevention layers provides a framework for resource allocation and cultural enhancement to control COVID-19. For instance, one study proposed a system model for COVID-19 crisis management using bow-tie analysis and defense layer analysis concepts from safety engineering. This model highlights seven defense layers designed to interrupt the disease transmission chain, ultimately reducing the burden on diagnostic and treatment systems. Implementing such a model not only safeguards public health but also improves the occupational safety of healthcare workers [2]. According to this model, the COVID-19 crisis has a medical surface but a systemic core. Effective management therefore requires systemic solutions, particularly focusing on modifying individual behaviors to minimize person-to-person contact. Defense layers must function efficiently to reduce the number of patients entering the healthcare system. Studies [3-13] emphasize the role of training programs in COVID-19 prevention and control. Additionally, research [14-16] highlights measures such as isolation protocols, exposure control, national systems for joint prevention, staff response mechanisms, combined medical and non-medical strategies, and transparent communication of pandemic information as critical mitigation strategies. Furthermore, studies[17-19] noted that older workers take fewer sick leaves compared to younger employees, suggesting that employers should ensure adequate sick leave for infected older workers to prevent workplace transmission. Finally, geographic factors have also been identified as significant influences in COVID-19 prevention and control, as discussed in studies [20,21].

While numerous studies have explored individual and systemic measures to control the spread of COVID-19, there is a lack of a comprehensive framework for systematically prioritizing these measures. **Objectives:** This study addresses this gap by employing fuzzy DEMATEL-BAYESIAN modeling to evaluate and rank the effectiveness of preventive and mitigative strategies.

Materials & Methods

Identification of effective factors in preventing and reducing COVID-19: This study involved a comprehensive electronic search of published research from January 1, 2020, to October 2021, focusing on methods to control COVID-19 infection and identify key factors in preventing its spread. Databases searched included Google Scholar, Scopus, PubMed, and Web of Science. Articles retrieved during the search were systematically reviewed for thematic relevance. Boolean search operators, particularly "AND," were employed to connect keywords and refine the search. Keywords included "protection layer and COVID-19," "safety barrier and COVID-19," "safety protection and COVID-19," "prevention layers and COVID-19," and "influence factors in the reduction of COVID-19."

All relevant studies identified were downloaded and organized in EndNote software to avoid duplication. To filter unrelated articles, an initial screening was conducted based on titles and abstracts. Subsequently, a secondary screening involved a full-text review to identify the most relevant studies.

Data from the eligible studies were extracted into an Excel spreadsheet. Information gathered included the authors, study location, publication date, identified factors contributing to COVID-19 prevention or reducing mortality and transmission, a summary of the findings, and references. The results of the review were categorized into two main groups: "before affliction" and "after affliction," representing preventive measures and post-infection management, respectively.

Determining the relationship between effective factors in preventing and reducing COVID-19 using fuzzy DEMATEL: Considering the potential cause-and-effect relationships among the factors influencing the prevention and mitigation of COVID-19, it is essential to identify these factors and their impact on the likelihood of key events in both the short and long term. To analyze these relationships systematically, the Fuzzy DEMATEL method was employed. This approach was originally developed by Fontella and Gabos in 1973 at the Battle Institute [22,23]. The DEMATEL method uses expert judgment to extract system factors and applies the principles of graph theory to systematically structure them. This process results in a hierarchical representation of system factors, highlighting their influence, interconnections, and the intensity of these relationships. DEMATEL was specifically designed to address complex global challenges by organizing and structuring assumed data, evaluating the intensity of interactions through scoring, and analyzing feedback loops alongside their relative importance. Notably, this method accommodates non-transferable relationships, making it particularly suitable for intricate systems.

However, estimating expert opinions with precise numerical values is challenging, especially under uncertain conditions. The outcomes of decision-making processes often rely heavily on subjective judgments that may be imprecise or ambiguous. This limitation underscores the necessity of incorporating fuzzy logic into the DEMATEL model [24]. The Fuzzy DEMATEL method effectively transforms the interrelationships and mutual influences among factors into a rational structural model of the system. This enables a clearer understanding of the dynamics at play, facilitating more informed decision-making in the context of COVID-19 prevention and control.

Phases of the fuzzy DEMATEL method:

Step 1: Designing fuzzy linguistic criteria

After identifying the factors influencing the prevention and mitigation of COVID-19 in the previous stage, a fuzzy DEMATEL questionnaire was developed and distributed to experts in the field, including university faculty members. These experts, leveraging their knowledge, experience, and access to information, assigned weights to the identified factors. To facilitate this process, the indicator table proposed by Renjith et al. was utilized for determining factor weights [25] (Table 1). The scoring of the selected experts was based on their characteristics, with the final weight for each expert calculated by dividing their score by the total score of all participating experts. To ensure consensus among the experts, the linear survey method suggested by Coleman and Winker was employed. This approach allowed for a structured aggregation of expert opinions, enhancing the reliability of the weighting process.[25]

Equation 1 $M_i=\sum W_i \ A_{ij}$ (i=1, 2, 3,... , m)

where W_i is the weight of experts, A_i is the number of experts with weight W_i , is the linguistic terms of expert opinion i , and M_i is the consensus of experts' opinion.

According to the linguistic variables presented in Table 2, experts' opinion is determined using 5 verbal expressions from "no effect" to "very high effect", whose equivalent fuzzy numbers (l_{ij}, m_{ij}, u_{ij}) are also given in the last column of the table.

Step 2: preparation of the matrix of fuzzy direct relations.

Table 1) Determination of weighted average indices(25)

Indicators	Rating	Score
Organizational position	Office Environment Manager	4
	Faculty Member	3
	Healthcare Staff	2
	HSE Supervisor/Officer	1
Work Experience	> 30 years	4
	20 to 30	3
	10 to 20	2
	5 to 10	1
Education Level	Ph.D.	5
	Master's degree	4
	Bachelor's degree	3
	Associate Degree	2
	diploma	1
Age	> 50 years	4
	40 to 50	3
	30 to 40	2
	< 30 years	1

Table 2) Linguistic scale for pairwise comparisons (23)

Linguistic variable	Definitive equivalent	Fuzzy equivalent
No effect	0	(1, 1, 1)
Low impact	1	(2, 3, 4)
Medium effect	2	(4, 5, 6)
High effect	3	(6, 7, 8)
Very high effect	4	(8, 9, 9)

To examine the internal relationships between the effective risk factors, experts were asked to make pairwise comparisons between the effective risk factors in terms of the effect of factor in the row on factor *j* in the column.

Then, by using the simple fuzzy average method to aggregate the opinion of experts, the fuzzy direct correlation matrix $\tilde{A}$ is formed [23].

Equation 2 $\tilde{A}=[\tilde{x}_{ij}]_{(n\times n)}$

If there are n experts and each row of the fuzzy direct matrix is represented by $\tilde{x}_{ij}$, $\tilde{x}_{ij}$, is calculated as follows [23]:

Equation 3 $\tilde{x}_{ij}=((\sum l_{ij}/n,\sum m_{ij}/n,\sum u_{ij}/n)$

In order to calculate the reliability of the samples, the inconsistency rate is calculated from the following equation [23]:

Equation 4 $$\text{Inconsistency rate}\,(\%) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|\frac{t_{ij}^{n}-t_{ij}^{n-1}}{t_{ij}^{n}}\right| \times 100\%$$

n is the number of samples and t_{ij}^{n} n is the average effect of criterion i on criterion j. The suggested reliability of the inconsistency rate is less than 5%.

Step 3: Normalize the fuzzy direct correlation matrix.

To normalize the values, $\sum u_{ij}$ of each row should be calculated and obtained by dividing the matrix $\tilde{X}$ by the maximum values $\sum u_{ij}$ of the fuzzy normal matrix $\tilde{N}$[23]:

Equation 5 $$k = \left(\sum_{j=1}^{n} u_{ij}\right)$$

Equation 6 $$\tilde{N} = \frac{1}{k}\times \tilde{X}$$

Equation 7 $$\tilde{N} = [\tilde{e}_{ij}]_{n\times n}$$

Equation 8 $$\tilde{e}_{ij} = (e_{ij}^{l},\ e_{ij}^{m},\ e_{ij}^{u})$$

Step 4: calculation of the complete fuzzy relation matrix. In order to calculate the complete correlation, first an Identity matrix is created. Then this Identity n*n matrix is normalized minus the matrix and the resulting matrix is inverted. The normal matrix is multiplied by the matrix to obtain

Equation 9 $$\tilde{T} = [\tilde{t}_{ij}]_{n\times n}$$

$$\tilde{t}_{ij} = (t_{ij}^{l},\ t_{ij}^{m},\ t_{ij}^{u})$$

Equation 10 $$T^{l} = N^{L}\times (I-N^{l})^{-1}$$

Equation 11 $$T^{m} = N^{m}\times (I-N^{m})^{-1}$$

Equation 12 $$T^{u} = N^{u}\times (I-N^{u})^{-1}$$

the complete fuzzy correlation matrix $\tilde{T}$. Each root of that fuzzy number is as follows [23]:

Step 5: de-fuzzing the values of the complete fuzzy relation matrix. In this step, the fuzzy numbers obtained from the previous steps are de-fuzzified according to the following

Equation 13 $$B = \frac{l_{ij}^{t} + 2\times m_{ij}^{t} + u_{ij}^{t}}{4}$$

formula: $\tilde{T}=[\tilde{t}_{ij}]_{(n\times n)}$ and entered in the complete correlation matrix with definite numbers $T=[t_{ij}]_{(n\times n)}$ [23].

Defuzzied B is the triangular fuzzy number $\tilde{t}_{ij}=(l_{ij}^{t}, m_{ij}^{t}, u_{ij}^{t})$ of the matrix $\tilde{T}$.

Step 6: obtaining the sum of the rows and columns of the matrix $\tilde{T}$. . The sum of rows and columns is obtained according to the following formulas [23]:

Equation 14 $\tilde{D}=(\tilde{D}_{i})_{n\times 1}=[\sum_{j=1}^{n}\tilde{T}_{ij}]_{n\times 1}$

Equation 15 $\tilde{R}=(\tilde{R}_{i})_{n\times 1}=[\sum_{i=1}^{n}\tilde{T}_{ij}]_{1\times n}$

$\tilde{D}$ and $\tilde{D}$ are n×1 and 1×n matrix, respectively.

Step 7: drawing a map of network relations.

In this step, the importance of indicators ($\tilde{D}+\tilde{R}$) and the relationship between them ($\tilde{D}-\tilde{R}$) are drawn, which is actually the basis for decision-making. If $\tilde{D}-\tilde{R}> 0$, the corresponding criterion is effective, and if D˜-R˜ <0, the corresponding criterion is impressionable [23].

Step 8: Threshold calculations.

All determined complete correlation values that are less than the average of the complete correlation matrix is identified and set to zero using the following formula. It means that the causal relationship is not considered [23].

Equation 16 $$TS = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} V_{ij}}{m \times n}$$

Equation 17 $$U_{ij} = \begin{cases} V_{ij} & V_{ij} \geq TS \\ 0 & \text{Others} \end{cases}$$

Modeling using Bayesian network: In this phase, the effective factors for preventing and mitigating COVID-19 infection, identified through the output of the DEMATEL analysis from the previous stage, were incorporated into a Bayesian network. To complete the conditional probability tables required for the Bayesian network, the factors' weights were determined using the Analytic Hierarchy Process (AHP) method, which involved pairwise comparisons of the factors. Once the weights were established, the conditional probability tables were generated using appropriate formulas within the Netica software, enabling the integration of the factors into a probabilistic framework. This approach facilitated a structured and quantitative analysis of the interdependencies between the factors influencing COVID-19 prevention and reduction.

Determination of the weight of variables using AHP

Step 1: Determination of the effective factors in preventing and reducing the disease of COVID-19.

In the previous phase of the study, the key factors influencing the prevention and reduction of COVID-19 were identified, and the interrelationships between these factors were determined.

Step 2: Formation of the experts' team and pairwise comparisons.

In this step, pairwise comparisons were developed based on the model established in Step 1. Pairwise comparison is a method used to assess the relative importance of research criteria. Using the 9-point scale of the Analytic Hierarchy Process (AHP), the pairwise comparisons were conducted by a group of experts (see Table 3). The team comprised 10 experts, including two infectious disease specialists, two nurses, four academic staff members from the University of Medical Sciences, and two occupational health specialists. The AHP methodology was employed to analyze and structure the experts' responses.

Step 3: Merging the matrices of pairwise comparisons using the geometric mean method

The geometric mean method was used to merge the opinions and convert them into a matrix. In this way, the comparisons were merged and became a pairwise comparison case.

Step 4: geometric mean of the rows.

In this step, the geometric mean of the lines should be calculated based on the following relationship[26]:

Step 5: Multiplying the geometric mean of the rows by the inverse of the sum of the geometric mea

Table 3) Verbal expressions and equivalent numbers

Verbal expression	Likert scale
Equal preference	1
Low to moderate preference	2
Moderate preference	3
Moderate to high preference	4
High preference	5
High to very high preference	6
Very high preference	7
Very high to great preference	8
Absolutely great preference	9

Equation 18 $\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{P}_{ij} \right)^{\frac{1}{n}} \qquad i = 1,2,3 \ldots, n$

In this step, the geometric mean calculated in the previous step is added together, then each geometric mean is multiplied by the inverse of this sum.

Equation 19

Step 6: Normalizing the weights of the criteria with the linear normalization method.

In this step, we divide each weight of the

$$w_i = r_i \otimes (r_1 \oplus r_2 \oplus \ldots \oplus r_m)^{-1}$$

previous step by the total weight to obtain the normalized weight.

Step 7: Examining the inconsistency rate of pairwise comparisons.

One of the important steps in the Analytic Hierarchy Process is to calculate the inconsistency rate. This rate must always be smaller than 0.1 so that the comparisons have proper consistency, and if this rate is greater than 0.1, the comparisons should be revised. The AHP inconsistency rate indicates whether the pairwise comparison was performed correctly [27]. suggested to check the compatibility, two matrices (the middle number and the approximate fuzzy number) are derived from each matrix, and then the compatibility of each matrix is calculated based on the hourly method. If the incompatibility index is less than 10%, the matrix is compatible. If it is more than 10%, the decision-maker is requested to reconsider the presented priorities.

Bayesian network : First, the Bayesian network was created using the output of the DEMATEL method, then conditional probability tables were created in the Bayesian network for the variables using the weight of the factors that were determined using the AHP method. Netica software was used to build the Bayesian network.

Bayesian network shows the dependence between a set of variables. Graphs are made up of nodes and edges that connect them. Each mutable node has a probability table or conditional probability tables (CPTs). There are parent and child nodes where the value or state of the variable of the parent node affects the state or value of the variable of the child node. As a result, to avoid circular reasoning, there should be no return to the previous node at the edge of the graph. A root node has no parent nodes. The root node is the beginning of the chain, and no other variable affects it. A "leaf" node has no child nodes, so it does not affect other variables. In a chain of nodes, if a node comes before another in the chain, it is called an ancestor node, and if it comes after other nodes, it is called a descendant node. All nodes that are not root nodes or leaf nodes are intermediate nodes. The root nodes represent the initiating or base events, and the leaf nodes represent the final effects or consequences. In the figure below, nodes A, B, and D, are the root nodes. G and H are leaf nodes. Nodes A and B are parents of C. Nodes C and D are the parents of E, which is also the parent of F, and G. Node F is the parent of node H (Figure 1).

The Bayesian network facilitates the understanding of the state of node H, which in turn

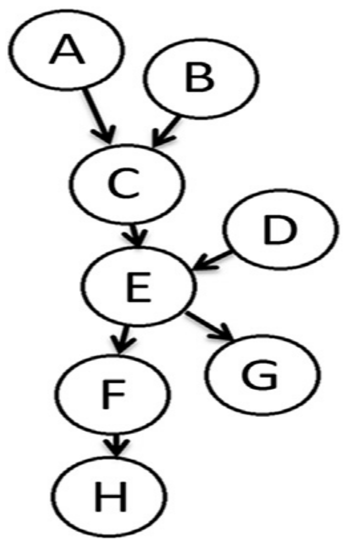

Figure 1) Bayesian graph

enhances our knowledge about state F. Additionally; by considering the states of nodes F and G, we can further improve our understanding of node E. In Figure 1, nodes C, E, and F are intermediate nodes, while nodes F, G, and H are descendants of node E[28].

Bayesian networks are a powerful tool for representing unknown knowledge and integrating statistical methods for data analysis with artificial intelligence techniques.

These networks have been successfully applied in various fields. Bayesian network models can serve multiple purposes, including forecasting, scenario analysis, diagnosis, data exploration, summarizing knowledge, identifying key data gaps, and supporting both individual and collaborative decision-making [29].

In this study, after constructing the Bayesian network, conditional probability tables (CPTs) were generated for the factors using the formulas presented in Table 4 in Netica software. As shown in the conditional probability formula, the variables are assumed to follow a normal distribution. For instance, the CPT for the prevention and reduction of COVID-19 nodes includes seven parent variables, each with five possible states: "very high," "high," "moderate," "low," and "very low." When the state of a parent node changes, the state of its child node is also affected. The influence of parent nodes on the child node varies depending on the weight assigned to each node.

Sensitivity analysis and validation of Bayesian network: In this phase, the sensitivity of the developed model was evaluated, followed by the updating of probabilities by altering the state of the nodes.

When developing a new model, rigorous validation is essential to ensure its robustness. In this study, sensitivity analysis was conducted to assess the proposed model. A model is considered robust if its results remain consistent, showing sensitivity without abrupt changes due to minor adjustments in

Table 4) Creating a conditional table using formulas in Netica software

Bayesian network nodes	Conditional probability table formula
Prevention and control of COVID-19	p (Prevention_reduction_covid | Personal_protective_equipment, Social_distancing, Geographic_factors, Learning_from_past_events, Technology, Attention_to_sensitive_groups,Training)- NormalDist (Prevention_reduction_covid, (0.119*Personal_protective_equipment+0.163* Social_distancing+0.064*-Geographic_factors+0.133*Learning_from_past_events+0.134*Technology+0.154*Attention_to_sensitive_groups+0.233*Training),0.1)
Social distancing	p (Social_distancing | Personal_protective_equipment, Geographic_factors, Learning_from_past_events, Technology, Attention_to_sensitive_groups,Training) = NormalDist (Social_distancing, (0.08*Personal_protective_equipment +0.04*Geographic_factors+0.15*Learning_from_past_events+0.36*Technology+0.07*Attention_to_sensitive_groups+0.3*Training),0.1)
Personal protective equipment	p (Personal_protective_equipment | Training, Attention_to_sensitive_groups, Technology, Learning_from_past_events) = NormalDist (Personal_protective_equipment, (0.55*Training +0.11*Attention_to_sensitive_groups+0.13*Technology+0.22*Learning_from_past_events),0.1)

the input parameters [30,31].

To identify the sensitive nodes in the proposed Bayesian network, the best and worst-case scenarios for each node were used as input evidence. For instance, the best state for a training node is to assign it the “very high” state. During the sensitivity analysis, other nodes remain unchanged, with no evidence being updated except for the node under test.

Determining the posterior probability of effective factors in preventing and reducing the disease of COVID-19 using Bayesian network: Probability updating is a critical application of the Bayesian network, which occurs when new information (evidence) is obtained. Evidence typically involves observing the status of the effective factors in the study area. In probability update analysis, the evidence propagates through the network, extending to the root nodes of the Bayesian network to update their prior probabilities using Bayesian inference. Conversely, by knowing the status of the factors influencing the prevention and reduction of COVID-19 in a society, the status of COVID-19 prevention and control in that society can be predicted. By updating the probabilities, the effective factors are prioritized, offering insights into their relative importance.

Findings

Main factors of prevention and control of COVID-19: For this study, a total of 1,151 articles were initially downloaded based on the selected keywords. After reviewing and matching the text of each article with the keywords, 272 articles were retained, while 877 were excluded. Further scrutiny of the full texts resulted in the final selection of 84 articles that met the study criteria, with 190 articles discarded, including 12 duplicates. The classification details are presented in the chart in Figure 2.

Main factors of prevention and control of COVID-19 are given below:

Vulnerable groups in the COVID-19 pandemic: Studies [17-19] have highlighted elderly adults as particularly vulnerable members of the community in the fight against the COVID-19. These studies pointed out that older workers tend to receive less sick leave compared to younger individuals, and suggested that employers should provide sick leave for older workers in the event of illness to prevent further transmission. Other control measures recommended for this group included: 1) Strict adherence to social distancing and physical distancing guidelines, 2) Regular attention to hand hygiene and respiratory hygiene, 3) Frequent disinfection of surfaces, 4) Avoiding unnecessary travel and visits to hospitals, 5) Proper use of face masks, 6) Adoption of a healthy lifestyle, 7)

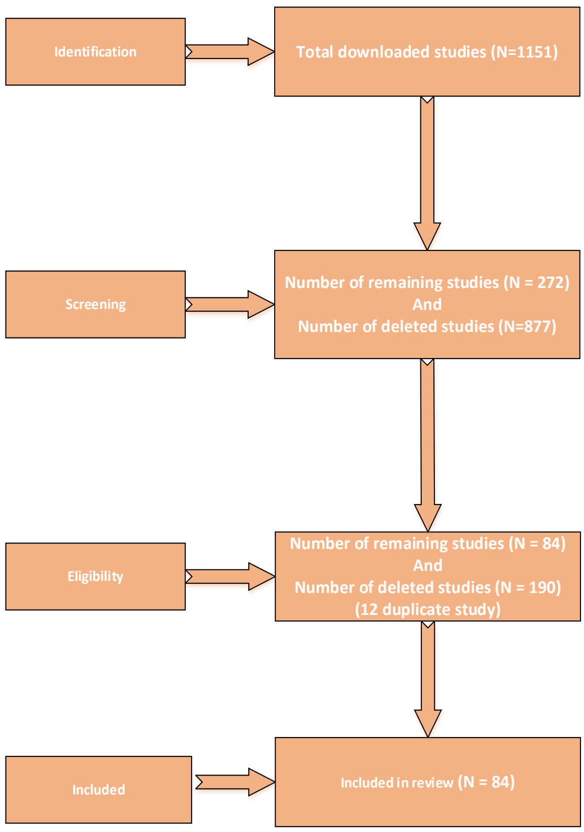

Figure 2) Flowchart for eligible articles determination

Early identification and isolation of infected elderly individuals, 8) Providing support and assistance to the elderly in the community, 9) Preventing infection in nursing homes, 10) Support from governments, civil society, and the general public during the COVID-19 pandemic, 11) Further research on the global impact of COVID-19 in nursing homes and among the elderly population, 12) Addressing economic risks, 13) Tackling delays in medical treatment, and 14) Overcoming challenges related to meeting basic needs.

Studies [32,33] also identified emergency workers as another vulnerable group within society. These studies focused on essential workers who continued to work full-time throughout the COVID-19 pandemic, some of whom are immigrants or foreigners without adequate government or domestic support. If they become infected, they may still be required to work, putting them at high risk of transmission and potentially exposing others to the virus. Special consideration should be given to ensuring sick leave, providing COVID-19-related special payments, offering benefits and protections for essential workers comparable to those of non-essential staff, guaranteeing a basic income, offering paid sick leave, providing health insurance coverage, and ensuring survival benefits. Additionally, strict regulations and standards should be established to prevent mortality and infection in the workplace.

Geographical (environmental) factors: Studies [20,21] identified geographical factors as significant determinants in the prevention and control of COVID-19. These studies indicated that temperature, relative humidity, and ultraviolet (UV) radiation had a more substantial impact on disease mitigation compared to other factors. Importantly, seasonality also played a role in these environmental effects. Higher relative humidity and lower maximum temperatures in summer were found to facilitate the spread of COVID-19, while UV radiation, similar to temperature and humidity, contributed to disease reduction. For example, increased solar radiation and temperature were associated with a decrease in COVID-19 transmission, indicating that UV radiation from the sun may help mitigate the virus's spread.

Lessons learning: Studies [34-42] highlighted South Korea's actions as one of the most successful examples of COVID-19 control and containment. South Korea implemented several key strategies, including establishing online platforms to track the virus's prevalence in local communities, providing real-time updates on morbidity and mortality rates, and distributing information on testing sites and mask availability. The country also adopted mobile text messaging, developed COVID-related apps, and took measures such as keeping borders open to foreign travelers who met strict health standards. Other interventions included the distribution of essential goods, the use of information and communication technology (ICT) in a four-stage algorithm for diagnosis, epidemiological research, patient management, and prevention, and collaboration with the private sector. Moreover, the government employed GPS tracking, bank card transaction monitoring, CCTV surveillance, and healthcare systems to track patient contacts and movement. While these strategies were effective, there were concerns regarding privacy violations, particularly related to the tracking of physical contacts, and thus, maintaining the confidentiality of personal information was recommended.

Studies [14-16] examined China's measures against COVID-19, which included strategies such as quarantine, isolation, exposure control, and a coordinated national prevention mechanism. Key actions involved the timely and transparent release of information, large-scale testing, and the deployment of medical staff according to local needs. The use of field hospitals, scientific research to understand the virus, and the provision of adequate personal protective equipment, such as high-standard masks, were also critical. Additionally, China's approach emphasized rapid mass-scale COVID detection tests and ongoing adjustments to control measures based on local conditions.

Study [43] explored the responses of various East Asian countries to the pandemic, noting that measures were tailored to each country's government structure, socio-economic conditions, and cultural context. The integration of emerging technologies alongside medical interventions played a key role in these responses.

Study [44] discussed India's response during the early stages of the pandemic, particularly concerning the country's large population and the increased demand for masks. As the supply of respiratory masks dwindled, an alternative was proposed: using transparent overhead projector (OHP) sheets to create makeshift masks and face shields for medical personnel.

Study [45] focused on workplace safety in Italy, where measures included job reorganization, social distancing, hygiene training, and regular disinfection to protect employees from the virus.

Study [46] compared the first and second waves of COVID-19 across European countries, identifying control measures such as general quarantine, physical distancing, and restrictions on hotels and public gatherings (e.g., fireworks during the New Year). Vaccination campaigns were also part of the response during subsequent waves.

Finally, study [47] argued that disaster control systems should be improved by learning from past events. The study emphasized the importance of resilience in managing disasters such as pandemics, concluding that resilience is a crucial concept for effective disaster control and optimal decision-making.

Training: Studies [3-13] have emphasized the importance of training in the effective control and prevention of COVID-19. Some key training areas identified include:

Job-specific training: Educating workers on the unique challenges of working during the pandemic, such as infection control protocols and safe practices.

Proper use of N95 masks: Training on extending the lifespan of masks during shortages by using them correctly.

Hand sanitizer usage: Teaching proper techniques for using hand sanitizers, especially in healthcare settings, to prevent transmission of the virus.

Cognitive and affective training for nursing students: Enhancing nursing students' abilities to manage the pandemic through online learning and scenario-based exercises.

Using trained dogs for diagnosis: Implementing trained dogs to detect COVID-19 in patients as a non-invasive diagnostic tool.

Standardized nursing terms: Developing common terminology for nurses to facilitate quick and clear communication during crises.

Simulation-based training: Using in situ simulation (ISS) to identify gaps in care and train health personnel in real-time scenarios, increasing their readiness and performance in critical situations.

Emergency response training: Providing emergency response training to medical staff to ensure proper management of COVID-19 cases, including how to wear personal protective equipment (PPE) correctly and avoid contamination.

Social media-based education: Leveraging social networks to train the public and healthcare workers about proper hygiene practices and avoiding contact with contaminated areas of the face.

Technology: The role of technology in COVID-19 mitigation has been explored in several studies [8, 10, 36, 39, 42, 43, 48-6] Technological applications for reducing and preventing the spread of the virus include:

Advanced face masks: Using specialized masks to minimize the transmission of airborne particles from infected individuals.

Artificial intelligence (AI): Implementing AI in drug detection, disease prediction, clinical diagnosis, and decision-making to improve the overall response to COVID-19.

Electrochemical ELISA technology: A rapid diagnostic tool for detecting SARS-CoV-2, enabling quick and accurate testing.

Social distancing technologies: Using AI and mobile apps to monitor and enforce social distancing guidelines.

Simulation technologies: Simulating COVID-19 scenarios for training medical staff to reduce stress and improve performance during actual outbreaks.

Face shields with heads-up displays (HUD): Providing medical staff with face shields equipped with HUDs to alert them of potential COVID-19 symptoms in real-time.

Information and Communication Technologies (ICT): Applying ICT in a four-stage algorithm for disease diagnosis, monitoring, epidemiological research, and patient management.

Silver nanoparticles: Investigating their potential in COVID-19 treatment to reduce virus replication and improve outcomes.

Virtual Reality (VR) and Augmented Reality (AR): Using VR and AR to train medical staff in COVID-19 crisis management and reduce training time.

Blockchain for privacy: Employing a blockchain-based framework to maintain patient anonymity while tracking contacts through cell phone Bluetooth.

Nanotechnology in drug development: Using nanotechnology to create drugs more effective against COVID-19.

Global health-fog system: An integrated system for diagnosing, treating, and preventing COVID-19 at a global scale.

Telemedicine: Enabling remote consultations between physicians and patients to reduce in-person interactions and increase social distancing.

Nanotechnology in PPE: Using polymer nanofibers in PPE production, such as respirators, to increase the effectiveness of protection.

Intelligent disinfectant robots: Deploying robots to disinfect environments without physical contact, preventing further spread of the virus.

Mobile applications for tracking contacts: Developing apps that trace individuals' interactions and potential exposure to COVID-19.

SEIQRD model: Implementing the SEIQRD (susceptible, exposed, infected, quarantined, recovered, deceased) model for risk management and prediction of COVID-19 outbreaks.

These technologies and training programs have significantly contributed to reducing the transmission of COVID-19 and improving overall pandemic response strategies.

Social distancing: A large body of studies [11, 13, 14, 17-19, 21, 32, 33, 35, 38, 42, 45, 46, 48, 49, 52, 59, 61, 62, 64, 66-76] has highlighted the importance of social distancing in preventing and controlling the spread of COVID-19. Key aspects and strategies related to social distancing include:

Smaller surgical teams: Reducing the number of team members in surgeries to maintain distancing within operating rooms.

Crowd management: Ensuring that crowded places, such as stores and indoor spaces, are well-managed to maintain physical distancing.

Sick leave for workers: Ensuring that workers who are sick are given appropriate sick leave to prevent transmission in workplaces.

Public transportation: Managing the public transportation system to minimize close contact between passengers.

TTI (Test, Trace, Isolate) policy: Implementing policies to test for asymptomatic cases, trace their contacts, and isolate those affected to reduce community transmission.

Use of artificial intelligence: Leveraging AI to enhance social distancing measures, such as monitoring movement or optimizing social distancing strategies.

Distance for vulnerable groups: Increasing the social distance specifically for the elderly and other vulnerable populations.

Outdoor presence: Encouraging outdoor activities to reduce the spread of the virus, which is more likely in indoor settings.

Time spent with others: Shortening the duration of interactions between people to reduce exposure.

Tracking physical contacts: Using mobile apps and technologies to track the interactions of people with confirmed cases.

Use of SEIQRD model: Employing the SEIQRD (susceptible, exposed, infected, quarantined, recovered, deceased) model to understand and manage the spread of the virus.

Movement control and crowd management: Enforcing restrictions on movement and limiting crowd sizes in certain areas to curb the virus transmission.

Intelligent disinfectant robots: Using robots to disinfect spaces, ensuring minimal human-to-human contact in public spaces.

Vacuum Exhausted Isolation Locker (VEIL): A technology designed to prevent airborne transmission of the virus in clinical settings.

Banning gatherings: Enforcing restrictions on gatherings in workplaces and public spaces to maintain social distance.

Work-from-home policies: Implementing work-from-home strategies where possible to reduce the need for commuting and in-office presence.

Tourism organization control: Limiting tourism and imposing strict controls on tourist movements during the pandemic.

Personal protective equipment (PPE)

The role of personal protective equipment (PPE) in controlling COVID-19 has been extensively discussed in studies [3, 4, 11, 13, 16, 18, 35, 44, 48, 53, 60, 63, 65, 68, 69, 72, 73, 75, 77-82] Key insights include:

Advanced face masks: Using specialized masks, such as N95, to reduce the transmission of airborne particles from infected individuals, especially in healthcare settings.

Combination of surgical and N95 masks: Recommending the use of both surgical masks and N95 masks for medical staff in operating rooms to enhance protection.

Access to PPE for healthcare workers: Ensuring that medical personnel have consistent access to high-quality PPE to avoid cross-contamination.

Training on PPE usage: Educating healthcare workers on the correct usage of N95 masks and other protective equipment, especially in scenarios with mask shortages.

PPE for vulnerable populations: Providing suitable PPE for the elderly and other vulnerable groups in the community to protect them from COVID-19.

HUD-equipped face shields: Using face shields with heads-up displays (HUD) that help medical personnel detect symptoms and protect them from airborne particles.

PPE distribution: Setting up mask distribution stations and PPE supply points in cities to ensure public access to protective equipment.

Nanotechnology in PPE: Using nanotechnology to enhance the effectiveness of PPE, such as incorporating nanofibers into masks and respirators to increase their protective capabilities.

Transparent OHP sheets: In cases of mask shortages, using transparent OHP (overhead projector) sheets to make makeshift face shields and masks.

Polycaprolactone (PCL) nanofibers: Incorporating PCL nanofibers into respirators for improved filtration and virus protection.

Job-specific PPE training: Providing specialized training to employees on how to wear PPE correctly and simultaneously in a way that maximizes protection.

Biological protection in labs: Employing biological protection equipment in settings like blood transfusion labs during the pandemic.

Figure 3 shows the number of studies mentioning each of the discussed factors—social distancing and personal protective equipment—directly or indirectly, providing a visual representation of the emphasis placed on these measures in the literature for COVID-19 prevention and control.

As shown in Figure 3, most studies have directly and indirectly mentioned the importance of social distancing, technology, and personal protective equipment (PPE) respectively in reducing and preventing the COVID-19 pandemic.

Determining the cause-and-effect relationships of effective factors in the prevention and control of COVID-19: At this stage, the cause-and-effect relationships among the factors influencing the prevention and control of COVID-19 were analyzed using the Fuzzy DEMATEL method. The expert specifications and corresponding weight factors are presented in Table 5. To assess the reliability of the experts' opinions, the inconsistency rate for the questionnaires was calculated using the Fuzzy DEMATEL approach. The average inconsistency rate was found to be 5%, indicating that the reliability of the experts' responses is 95%. The normalized matrix of relationships between the effective factors in the prevention and control of COVID-19 is shown in Table 6.

Table 7 shows the matrix of relationships between factors. According to table 7, attention to sensitive groups with D-R value of 0.559 is the most causal factor and

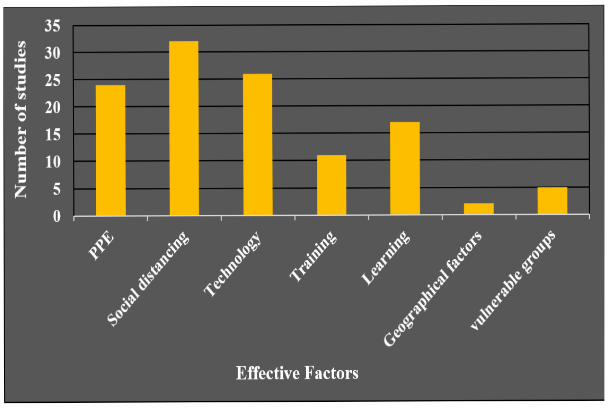

Figure 3) Number of studies that mentioned one of the main effective factors directly or indirectly

Table 5) Specifications and determining the weight factor of experts

No	Organizational position	Work experience	Training	Age	weighted score	Weight factor
1	3	4	5	4	16	0.137
2	2	1	4	2	9	0.077
3	3	2	5	2	12	0.103
4	3	2	5	2	12	0.103
5	3	3	5	2	13	0.111
6	3	1	5	2	11	0.094
7	3	4	5	4	16	0.137
8	3	3	5	4	16	0.137
9	2	2	5	3	12	0.103

Table 6) Normalized matrix of relationships between effective factors in the prevention and control of COVID-19

Normal	Personal protective equipment			Social distancing			Technology			Training			Lessons learning			Geographic factors			Attention to sensitive groups		
Personal protective equipment	0.00	0.00	0.00	0.15	0.18	0.19	0.12	0.14	0.16	0.15	0.17	0.18	0.10	0.13	0.15	0.07	0.08	0.10	0.13	0.15	0.17
Social distancing	0.15	0.17	0.19	0.00	0.00	0.00	0.11	0.13	0.14	0.15	0.17	0.19	0.12	0.14	0.16	0.09	0.11	0.13	0.14	0.17	0.18
Technology	0.13	0.15	0.17	0.14	0.17	0.19	0.00	0.00	0.00	0.11	0.14	0.16	0.09	0.11	0.13	0.10	0.12	0.15	0.12	0.14	0.17
Training	0.17	0.19	0.20	0.18	0.21	0.22	0.16	0.18	0.20	0.00	0.00	0.00	0.14	0.16	0.19	0.06	0.08	0.09	0.14	0.16	0.17
Lessons learning	0.15	0.18	0.20	0.14	0.17	0.18	0.10	0.12	0.14	0.13	0.15	0.17	0.00	0.00	0.00	0.05	0.07	0.09	0.12	0.15	0.17
Geographic factors	0.14	0.16	0.18	0.11	0.13	0.14	0.06	0.07	0.09	0.06	0.08	0.10	0.03	0.03	0.03	0.00	0.00	0.00	0.07	0.09	0.11
Attention to sensitive groups	0.13	0.16	0.17	0.14	0.16	0.18	0.10	0.12	0.15	0.13	0.16	0.18	0.12	0.15	0.17	0.07	0.09	0.11	0.00	0.00	0.00

social distancing with D-R value of 1.165 is the most influenced factor. Based on the threshold value, the causal relationships between effective in preventing and controlling COVID-19 are according to table 8. Figure 4 shows the relationship between the effective factors. The direction of the arrow indicates the influence of the factors.

Figure 5 illustrates the Cartesian coordinates of the factors influencing the prevention and control of COVID-19. Based on the figure, the factor with the highest causal influence is attention to sensitive groups, with a D-R value of 0.559. On the other hand, social distancing is the most influenced factor, with a D-R value of 1.165. Furthermore, social distancing is identified as the most important factor with a D+R value of 16.144, while geographical factors are the least important, with a D+R value of 11.455.

Weighting of factors using AHP: In the previous phase of the study, the relationship between effective factors in preventing and reducing the disease of COVID-19 was determined.

In this section, the weight of factors effective in preventing and reducing the disease of COVID-19 was determined using AHP. In total, the opinion of 10 experts was used. Table 9 shows the final weight matrix of the factors.

Table 10 shows the weight of factors effective in preventing and reducing the disease of COVID-19. According to the results of Table 10, training with a weight of 0.233 is in the first place, social distancing with a weight of 0.163 is in the second place, attention to sensitive age groups is in the third place with a weight of 0.154, and technology is in the fourth place with a weight of 0.134. Lessons learning with a weight of 0.133 is in the fifth

Table 7) Matrix of relationships between factors

Effective risk factor	R	D	D-R	D+R
Personal protective equipment	8.152	7.225	-0.927	15.377
social distancing	8.654	7.490	-1.165	16.144
Technology	6.886	7.113	0.227	13.998
Training	7.591	8.089	0.507	15.688
Lessons learning	7.121	7.110	-0.011	14.231
Geographic factors	5.448	6.007	0.559	11.455
Attention to sensitive groups	7.395	8.204	0.809	15.599

Table 8) Causal relationships between effective factors in the prevention and control of COVID-19

Effective risk factor	Personal protective equipment	Social distancing	Technology	Training	Lessons learning	Geographic factors	Attention to sensitive groups
Personal protective equipment	0	1	0	1	0	0	0
Social distancing	1	0	0	1	0	0	0
Technology	1	1	0	0	0	0	0
Training	1	1	0	0	0	0	1
Lessons learning	1	1	0	0	0	0	0
Geographic factors	0	1	0	0	0	0	0
Attention to sensitive groups	1	1	0	1	1	0	0

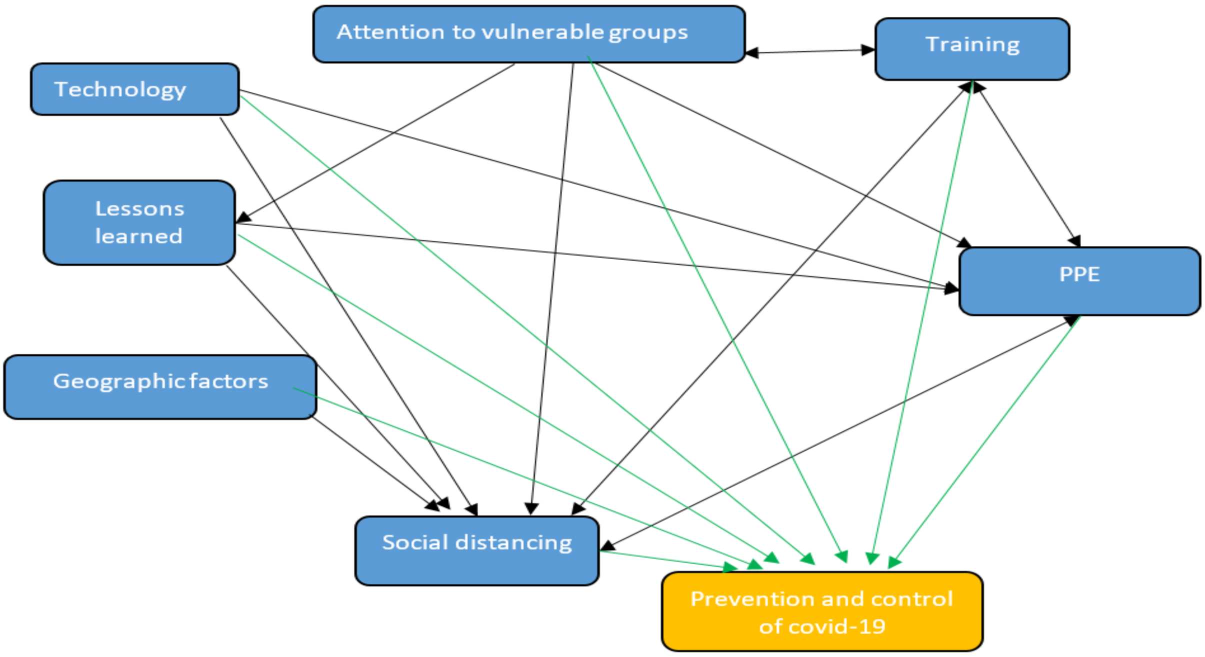

Figure 4) Causal relationship between effective factors in the prevention and control of COVID-19

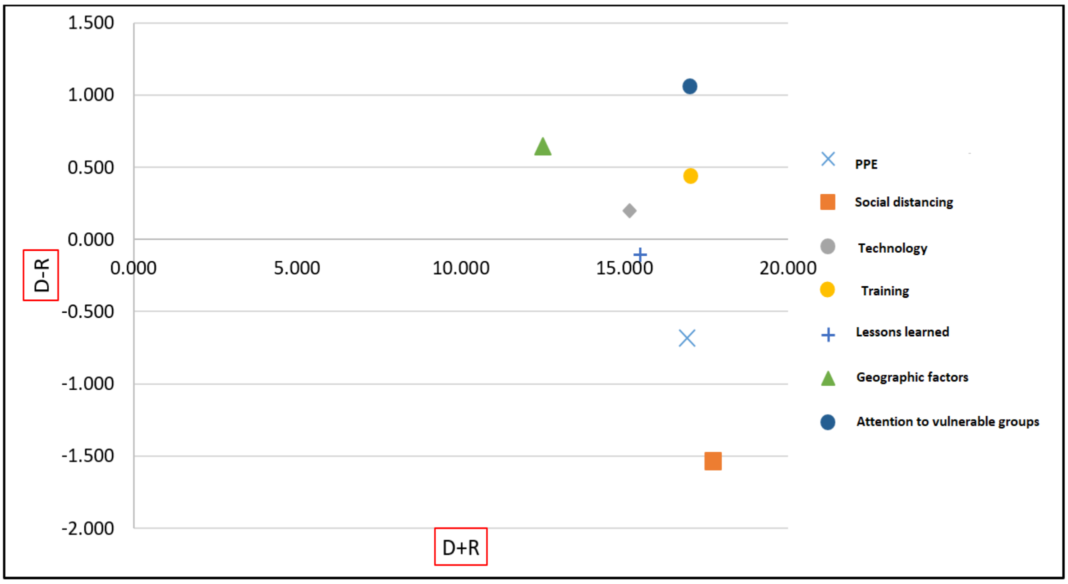

Figure 5) Causal relationship map of effective factors in the prevention and control of COVID-19

place, personal protective equipment with a weight of 0.119 is in the sixth place, and geographical factors with a weight of 0.064 are in the seventh place. The inconsistency rate was calculated to be 1.1%.

Figure 6 shows the effective variables in the prevention and control of COVID-19 along with their weights. Table 11 presents the weights of factors influencing social distancing. According to the results, technology ranks first with a weight of 0.36, followed by training in second place with a weight of 0.30. Learning from past events holds the third position with a weight of 0.15, while personal protective equipment ranks fourth with a weight of 0.08. Attention to sensitive age groups is in fifth place with a weight of 0.07, and geographical factors are

Table 9) Pairwise comparison matrix

No	Effective risk factors	Personal protective equipment	Social distancing	Technology	Training	Lessons learning	Geographic factors	Attention to sensitive groups
1	Personal protective equipment		0.66	1.11	0.44	0.88	2	0.77
2	Social distancing	1.5		1.25	0.66	0.875	2.8	1.25
3	Technology	0.88	0.8		0.6	1.14	1.66	1.2
4	Training	2.5	1.5	1.66		2	3	1.5
5	Lessons learning	1.125	1.14	0.875	0.5		2	0.8
6	Geographic factors	0.5	0.33	0.6	0.33	0.5		0.285
7	Attention to sensitive groups	1.285	0.8	0.83	0.66	1.22	3.55	

Table 10) Matrix of the final weights of the factors affecting the prevention and reduction of the COVID-19 disease

No	Effective risk factors	Final weight	Score
1	Personal protective equipment	0.119	6
2	Social distancing	0.163	2
3	Technology	0.134	4
4	Training	0.233	1
5	Lessons learning	0.133	5
6	Geographic factors	0.064	7
7	Attention to sensitive groups	0.154	3
8	inconsistency rate	% 1.1	

in the sixth position with a weight of 0.04. The calculated inconsistency rate for the results is 8% Figure 7 shows the variables affecting the social distancing factor along with their weights. Table 12 shows the weight of factors affecting personal protective equipment. According to the results of Table 12, Training with a weight of 0.233 is in the first place, social distancing with a weight of 0.163 is in the second place, attention to sensitive age groups is in the third place with a weight of 0.154, technology is in the fourth place with a weight of 0.134. Lessons Learning with a weight of 0.133 is in the fifth place, personal protective equipment with a weight of 0.119 is in the sixth place, and geographical factors with a weight of 0.064 are in the seventh place. The inconsistency rate was calculated as 6%. Figure 8 shows the variables affecting the factor of personal protective equipment along with their weight.

Construction of a Bayesian network and quantifying it: Based on the output of the previous phase of the study (DEMATEL), a Bayesian network was constructed. Figure 9 shows the constructed Bayesian network. As it shows, seven factors including personal protective equipment, social distancing, technology, Training, learning from past events, geographical factors, and attention

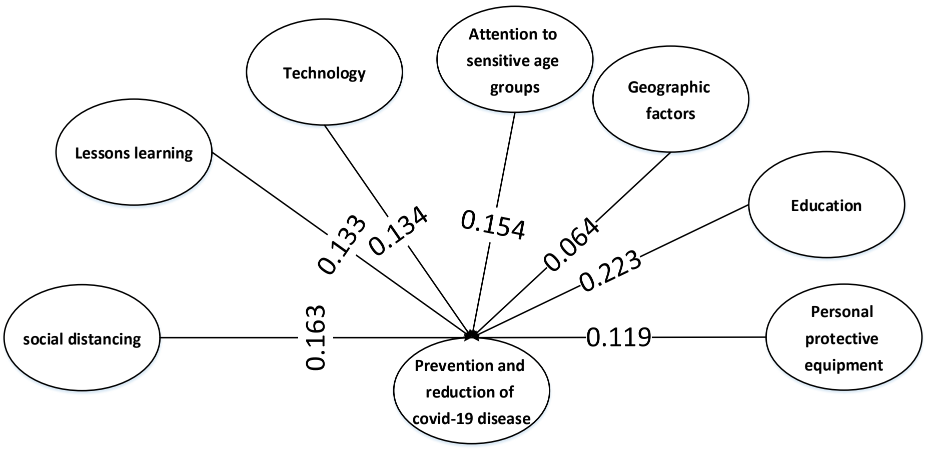

Figure 6) The final weight of factors affecting the prevention and reduction of the disease of COVID-19

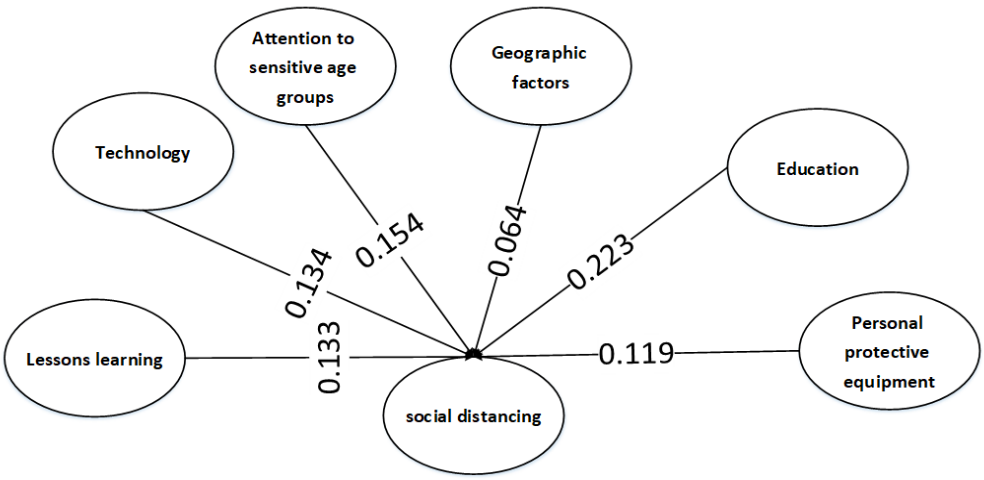

Figure 7) The final weight of factors affecting social distancing

Table 11) Matrix of final weights of factors affecting social distancing

No	Effective risk factors	Final weight	Rank
1	Personal protective equipment	0.08	4
2	Technology	0.36	1
3	Training	0.30	2
4	Lessons learning	0.15	3
5	Geographic factors	0.04	6
6	Attention to sensitive age groups	0.07	5
7	inconsistency rate	8%	

to sensitive age groups as parent nodes affect the factors of follow-up and control of COVID-19 as child nodes. Based on the internal relationships between the factors, six factors including personal protective equipment, technology, Training, learning from past events, geographical factors, and attention to sensitive age groups are effective on the social distancing factor. Also, four factors including Training, technology, learning from past events, and paying attention to sensitive age groups affect the factor of personal protective equipment. All nodes have 5 modes including “very high”, “high”, “moderate”, “low” and “very low”.

After the construction of the Bayesian

Table 12) Matrix of final weights of factors affecting personal protective equipment

No	Effective risk factors	Final weigh	Rank
1	Training	0.55	1
2	Technology	0.13	3
3	Lessons Learning	0.22	2
4	Attention to sensitive age groups	0.11	4
5	inconsistency rate	6%	

network, the conditional probability tables of the Bayesian network were completed and quantified based on the weights obtained from the AHP method and formula writing in the Netica software according to Table 4.

Model sensitivity analysis: The sensitivity analysis of the model when the parent nodes are in the worst state is shown in Figure 10. As shown, when the parent nodes are in the worst state, the child node is also in its worst state.

The sensitivity analysis of the model when

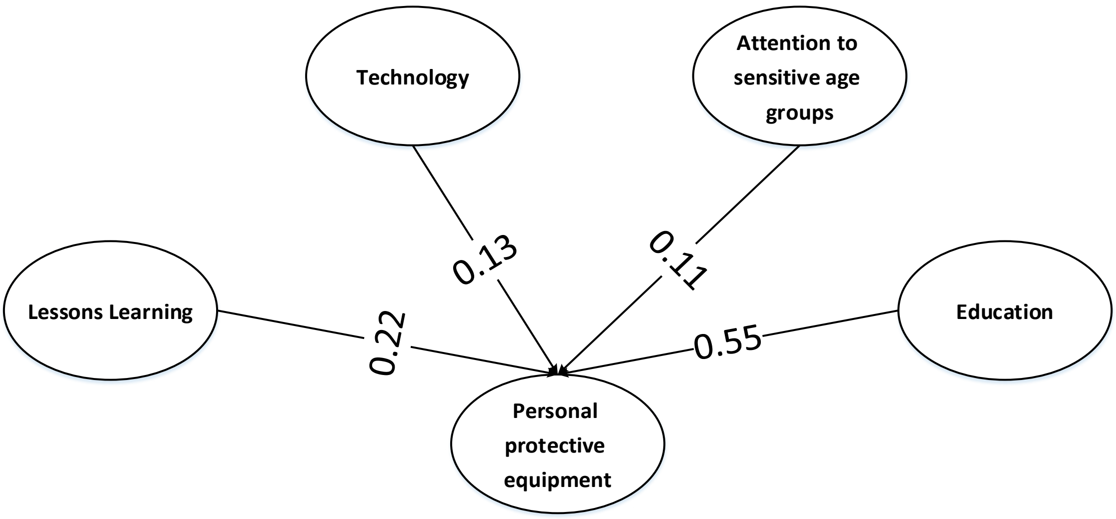

Figure 8) The final weight of factors affecting personal protective equipment

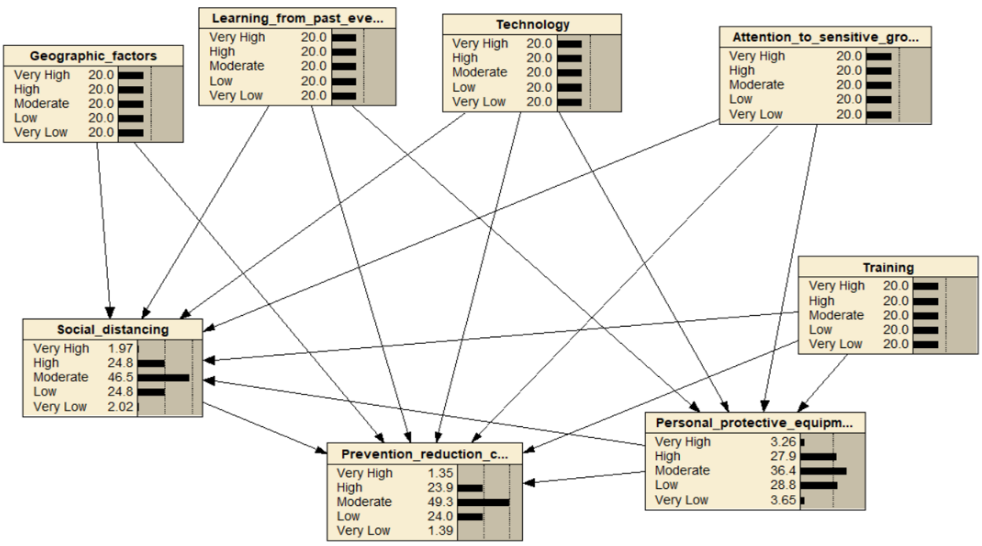

Figure 9) Bayesian network

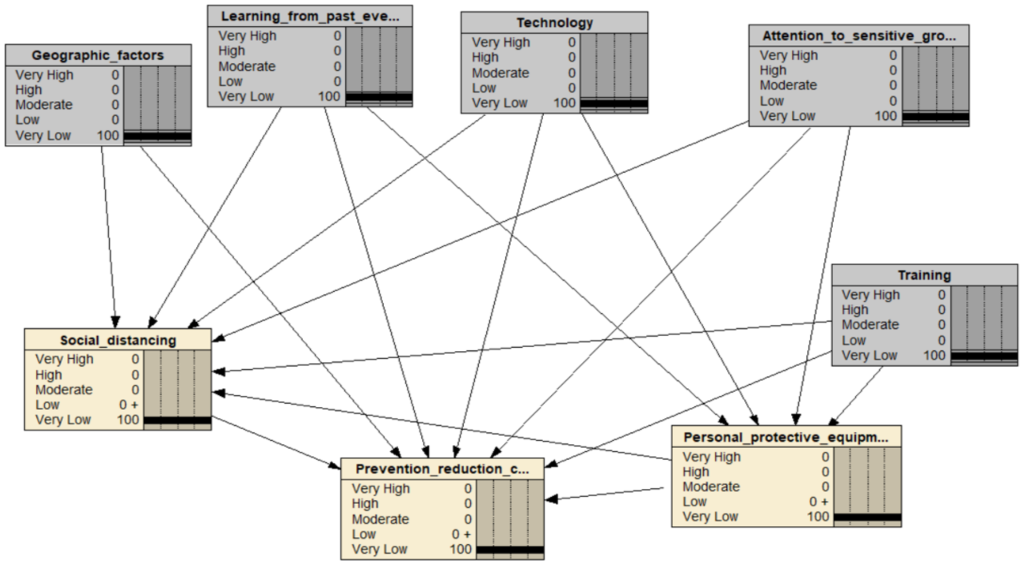

Figure 10) Sensitivity analysis of the model when the parent nodes are in the worst case

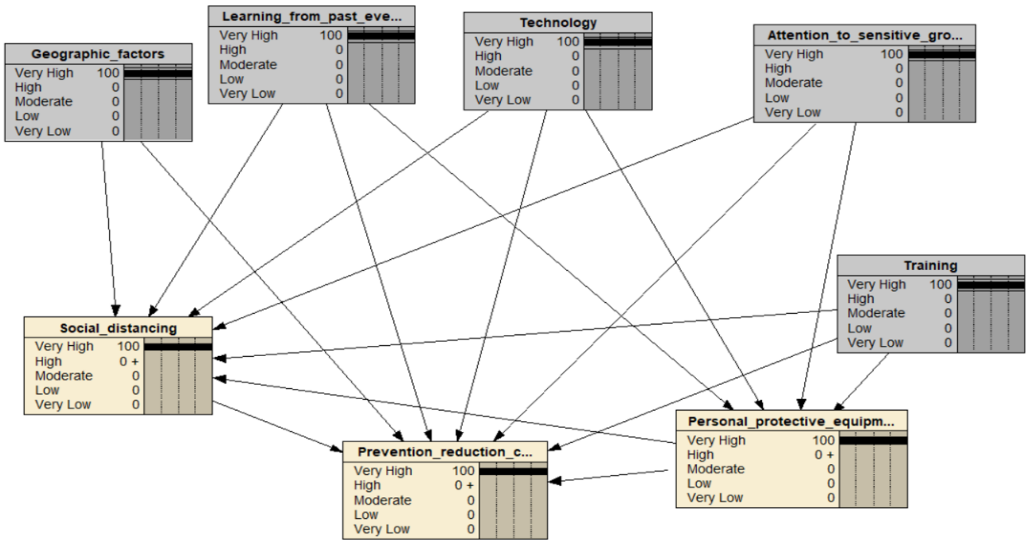

Figure 11) Sensitivity analysis of the model when the parent nodes are in the best state

the parent nodes are in the best state is shown in Figure 11. As shown, when the parent nodes are in the best state, the child node is also in its best state.

Table 13 illustrates the sensitivity of the COVID-19 prevention and reduction node in relation to other nodes. As shown, the sensitivity of the prevention and reduction node to social distancing is higher than that of the other factors. This indicates that, in order to prevent and reduce COVID-19, the top priority in decision-making should be focused on social distancing. Following that, the next priorities should be personal protective equipment, training, technology, lessons learned, attention to sensitive groups, and geographical factors.

Probability Update: Figure 12 shows the probability update using the Bayesian network diagnostic approach. In this scenario, the prevention and reduction of COVID-19 in society is considered under the worst-case conditions, where the status of the parent nodes is updated accordingly. As illustrated, to achieve a 100% reduction in COVID-19, social distancing should reach 92.7%, personal protective equipment should be at 92.3%, training at 92.3%,

Table 13) The level of sensitivity of the node of prevention and reduction of COVID-19 compared to other nodes

No	Node	Sensitivity level
1	social distancing	0.89949
2	Personal protective equipment	0.83660
3	Training	0.42008
4	technology	0.14417
5	lessons learning	0.09502
6	attention to sensitive groups	0.08060
7	geographical factors	0.01246

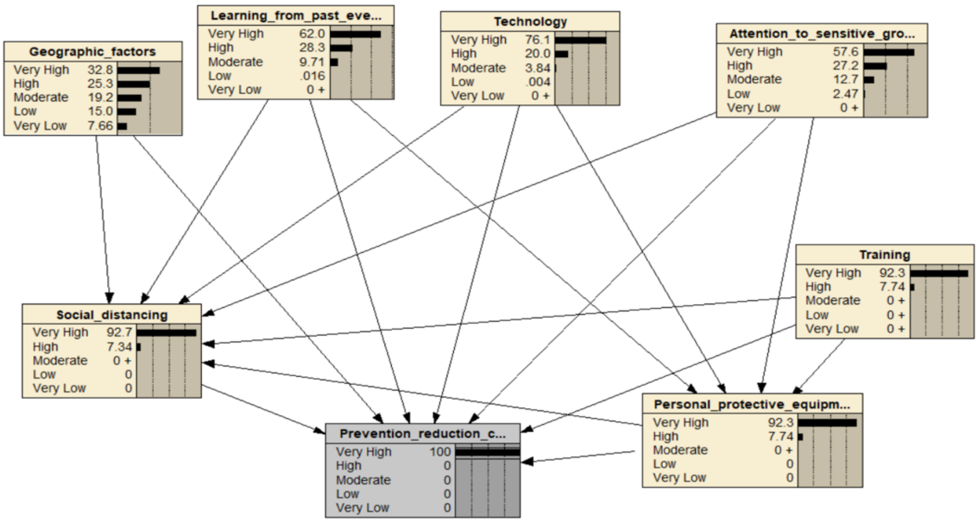

Figure 12) Updating the probability of parent nodes if the target node is in "very high" state

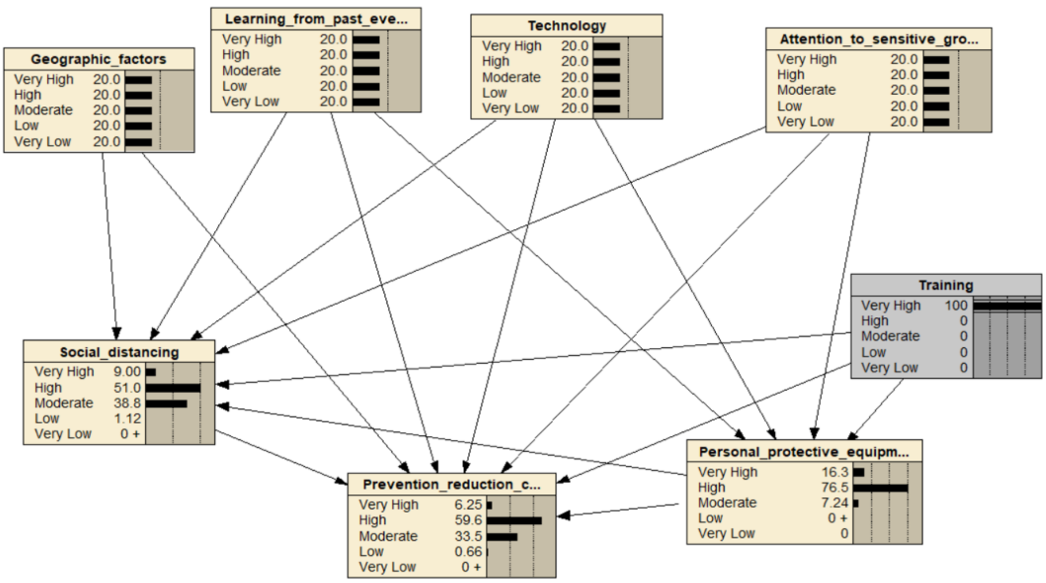

Figure 13) Updating the probability of prevention and management of COVID-19 when only the Training node is in "very high" state

technology at 76.1%, attention to sensitive groups at 57.6%, lessons learned at 62%, and geographical factors at 32.8% within society. Figure 13 shows the updated probability of prevention and management of COVID-19 when only the Training node is in the "very high" state, without changing the state of the other nodes. As shown, with complete Training, the probability of preventing COVID-19 is about 59.6% at the high level and 6.25% at the very high level.

Figure 14 shows the updated probability of prevention and management of COVID-19 when only the attention to sensitive groups node is in the "very high" state without changing the state of the other nodes. As shown, considering the susceptible groups as a complete node, the probability of preventing COVID-19 is about 37.9% at the high level and 3.9% at the very high level. Figure 15 shows the updated probability of prevention and management of COVID-19

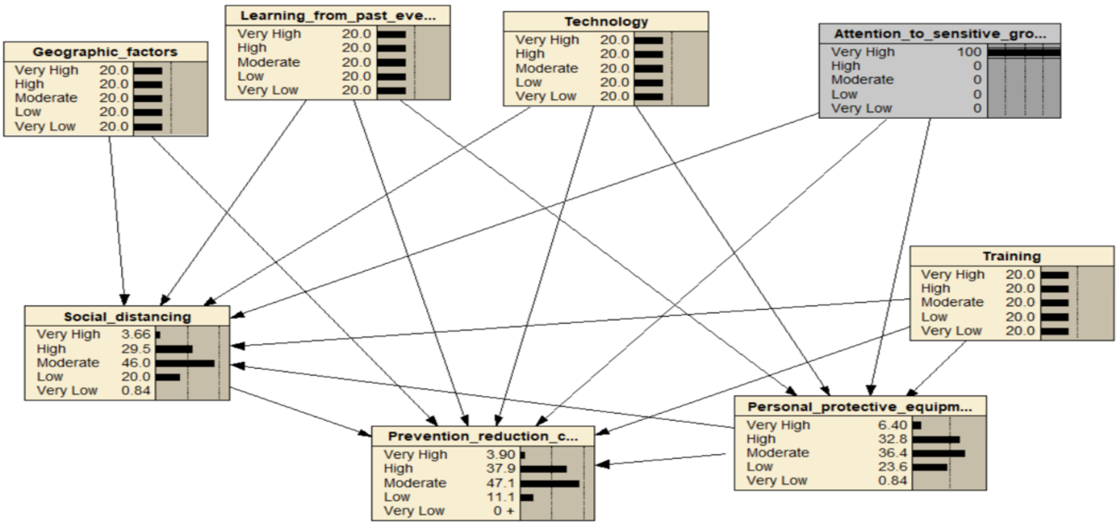

Figure 14) Updating the probability of prevention and management of COVID-19 when only the attention to the sensitive groups is in the "very high" state

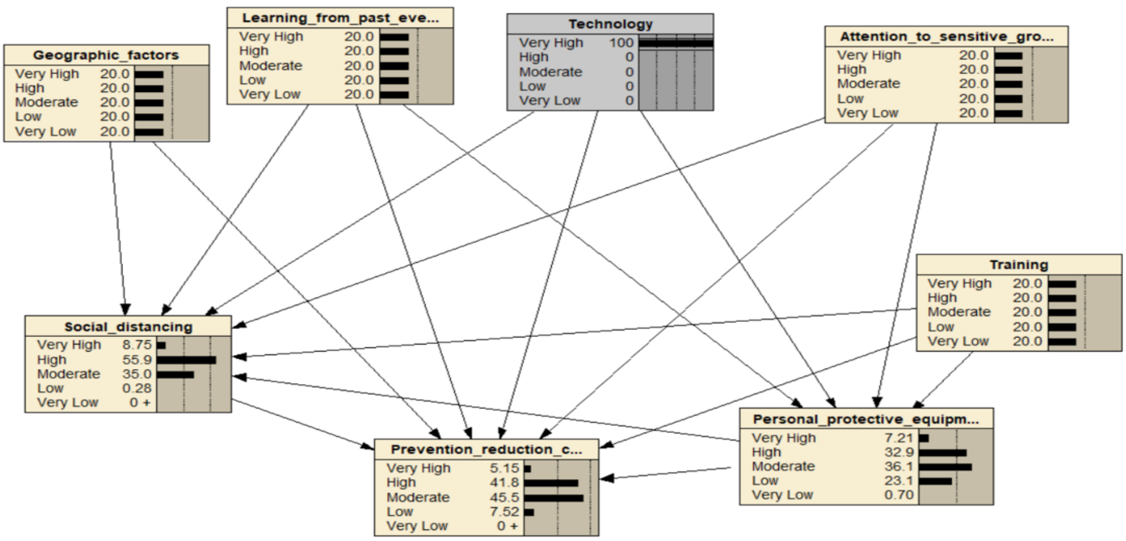

Figure 15) Updating the probability of preventing and managing COVID-19 when only the technology node is in the "very high" state

when only the technology node is in the "very high" state without changing the state of the other nodes. As shown, with the complete implementation of the technology, the probability of preventing COVID-19 is about 41.8% at a high level and 5.15% at a very high level.

Figure 16 demonstrates the updated probability of COVID-19 prevention and management when only the "lessons learning" node is set to the "very high" state, while the states of the other nodes remain unchanged. As shown, by fully considering lessons learned, the probability of preventing COVID-19 is approximately 38.6% at a high level and 4.20% at a very high level.

Figure 17 illustrates the updated probability of COVID-19 prevention and management

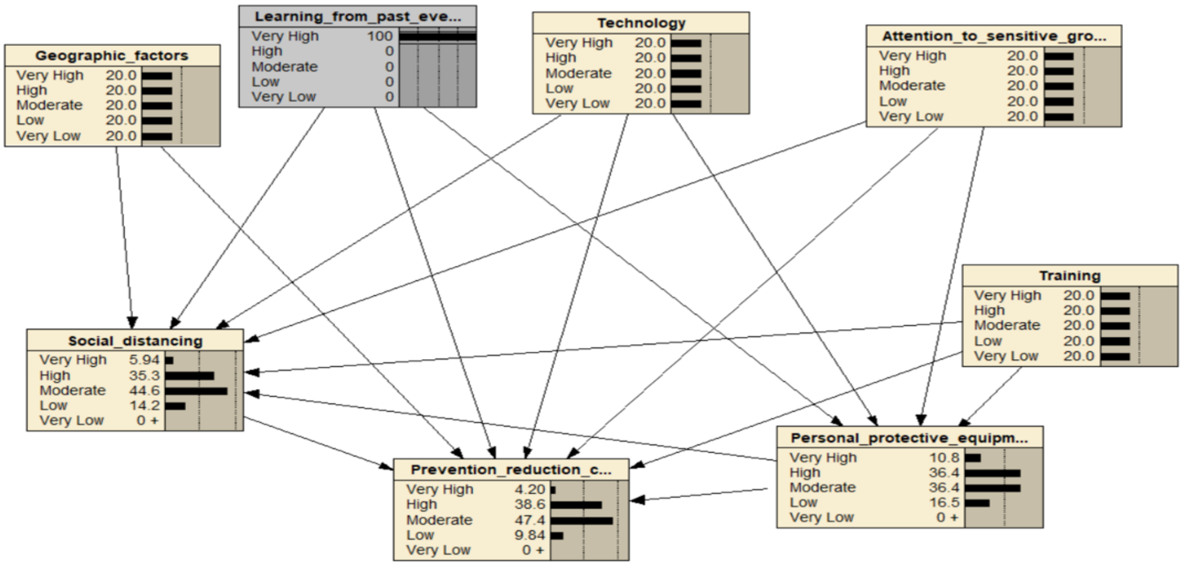

Figure 16) Updating the probability of preventing and managing COVID-19 when only the lessons learning node is in the "very high" state

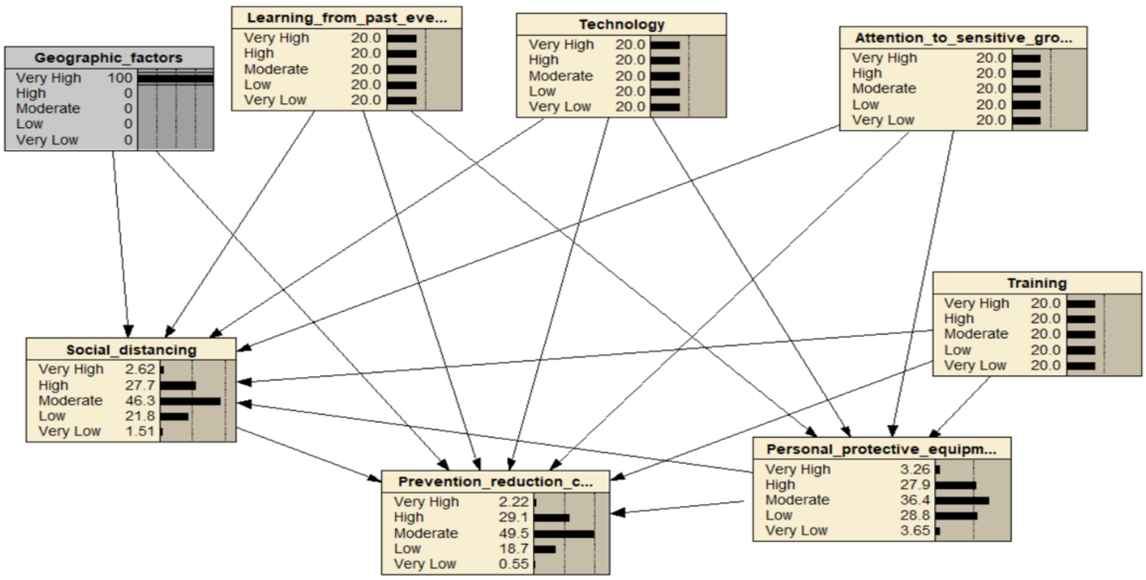

Figure 17) Updating the probability of prevention and management of COVID-19 when only the geographical factors node is in the "very high" state

when only the geographical factors node is in the "very high" state, while the states of the other nodes remain unchanged. As depicted, by fully considering geographical factors, the probability of preventing COVID-19 is approximately 29.1% at a high level and 2.22% at a very high level.

Discussion

This research offers important insights into the complex multidimensional and interrelated factors holding the key to preventing and controlling COVID-19. Apart from some methodologies such as fuzzy DEMATEL and AHP, drawing on a systematic review of 84 studies, this study not only identifies the most effective strategies for combating the pandemic but also explains them in the broader public health and policy contexts. A particularly salient finding is that priority protection has to be given to those groups most vulnerable, such as the elderly and essential workers, who have had to bear a disproportionate part of the pandemic's burden. Therefore, it becomes extremely insistent that the interventions targeted toward such groups are of prime importance since they are the single most important causal factor influencing the outcomes of COVID-19. An interpretation drawing from such an inference highlights the need for public health strategies tailored to have an effect beyond generic approaches. In particular, it should incorporate rigorous social distancing, hygiene practices, and isolation measures for the elderly, including financial and health protections for essential workers who often have to operate with little support. To control the transmission of COVID-19, China implemented strict measures starting with the lockdown of Wuhan on January 23, 2020, which delayed the virus's spread to other cities by 2.91 days. A nationwide emergency response followed, including suspending public transport, closing entertainment venues, and banning public gatherings. Cities that acted preemptively reported significantly fewer cases in the first week of their outbreaks. These measures collectively slowed the epidemic's growth. By February 19, 2020, they were estimated to have prevented hundreds of thousands of cases, demonstrating the effectiveness of early and comprehensive public health interventions [83]. Targeted strategies, therefore, reduce not only several immediate health risks but also the long-term socio-economic impacts on vulnerable populations.

The highest D-R value of 1.165 was obtained for social distancing, meaning this is the most influencing parameter in controlling the spread of COVID-19. This result shows just how much a reduction in physical interaction matters in bringing down transmission rates. This is further validated through sensitivity analysis, suggesting that social distancing should be the bedrock of any prevention strategy.

The Bayesian network analysis gives a nuanced interpretation, whereby it is clearly shown in the graph that social distancing works in a diffused manner, and this aspect gets significantly enhanced if combined with other measures like the use of personal protective equipment, technology, and training. In some ways, this interconnection implies that it would only be via a holistic approach—where multiple strategies are administered in concert—that the maximal effect of social distancing would be rendered. The policy implications are clear: rigorous implementation and support of social distancing measures with complementary tools and resources will yield optimal results. While geographical factors were rated as less critical in the AHP analysis, this does not mean they were not relevant. Keeping the impact of environmental factors like temperature, humidity, and UV radiation that influence viral transmission, the study looks at this factor to be explained by geographical factors. The role of geographical factors becomes more context-specific, suggesting that public health interventions should therefore be regionally tailored and adaptable to seasonal variation. This implies an interpretation where there is strong dynamism in context-sensitive planning of public health, so it can adjust to changes in the environment to optimize the effect of an intervention. To control the rapid spread of COVID-19, the Chinese government implemented strict lockdown policies starting in late January 2020. This study examines the relationship between geographic factors (latitude, longitude, and altitude) and cumulative infection numbers, as well as the role of population density in spreading speed during lockdown. Using data from December 8, 2019, to April 8, 2020, the study found a negative correlation between cumulative infections and latitude and altitude. Additionally, population density had minimal influence on the spread under strict lockdown measures. The findings suggest that China's lockdown policies effectively reduced the spread of COVID-19, regardless of geographic or population density factors [84]. Training is the major factor heading the weighting in the AHP analysis. The findings of this study indicate that effective training programs are essential to equipping health workers and the general public with appropriate knowledge and skills in the fight against COVID-19. A study found that sports closures during COVID-19 peaks in Italy negatively impacted young athletes' health without significantly reducing virus transmission. SARS-CoV-2 positivity rates were similar among those who participated in sports and those who did not, but athletes who continued organized training had a lower infection risk. Stopping sports was linked to a 1% BMI increase and reduced adherence to WHO physical activity guidelines, highlighting the unintended health consequences of restricting sports activities [85]. In this regard, it concerns more than direct implications about the proper use of PPEs and adherence to set health guidelines; rather, it gives broader implications for the reduction of clinical error and improvement of the quality of care generally. Additionally, technology has to be integrated into the dispensation of social distancing through telemedicine, tracking systems, and AI-driven diagnostic tools. One reading is that technology is not just a solution for immediate support of pandemic responses but has long-term transformational potential for healthcare delivery and sustainability. The study also calls for learning from others—South Korea and China—to learn about ICT-based solutions, comprehensive testing, and rigid quarantine measures that have been incorporated in containing the pandemic.

These case studies are, on the one hand, very valuable examples for countries looking to refine their public health strategy. On the other hand, ethical concerns ranging from privacy to balancing imperatives in public health with individual rights must be spotted and negotiated. One such interpretation would draw attention to the balancing act required on both fronts—that is, respecting ethical norms while vigorously pursuing public health measures. Bayesian network analysis modeled conditional probabilities of various strategies more precisely. The sensitivity analysis demonstrated that the most responsive social distancing practices are due to the prevention and reduction of COVID-19, followed by the availability and use of PPE and effective training. These findings can be interpreted as a suggestion that social distancing, PPE, training, and technology synergistically work together to accomplish a high level of prevention. This holistic perspective is what informs significant public health policy at this juncture: underlining the need for integrated strategies that focus on the strengths of different interventions. Policy and practice implications are profound.

These findings give way to the recommendation that social distancing needs to be factored in more at the policy level, especially with vulnerable groups, but with a wide accessibility of PPE and training. Greater use of technology in health strategies requires scaling up, learning from practices developed elsewhere proving effective, and tailoring them to the local context. The ethical implications, especially about privacy and distributive justice, would set the course for implementing the aforesaid strategies. The interpretation resettles the need for a nuanced, ethical approach to public health policy that balances urgency and long-term implications for society.

Regarding the limitations of the study, the selected articles might have incomplete information. Moreover, DEMATEL and AHP methods are also connected with some expert opinion bias. Such limitations point to further research that could be done concerning the long-term results of the identified interventions and the changing nature of the virus, especially through new variants. In this manner, the implication is a call for further investigation and adaptation of strategies so that responses remain current and effective in public health amidst changing circumstances.

Conclusion

The purpose of this research was to identify and prioritize measures to prevent and reduce the spread of the COVID-19 using fuzzy DEMATEL-BAYESIAN modeling. In the first phase, effective factors in preventing and reducing the disease of COVID-19 in past studies were examined and extracted. In the second phase, the cause-and-effect relationships of the effective factors in the prevention and control of COVID-19 were determined using the fuzzy DEMATEL method. In the third phase, first, the effective factors for preventing and reducing the infection of the COVID-19 were entered into the Bayesian network according to the output of the previous phase. Then, to complete the conditional probability table for the Bayesian network, the weight of the factors affecting the prevention and reduction of the COVID-19 was carried out using the Analytical Hierarchy Process (AHP) and pairwise comparison of the factors. In the fourth phase, the sensitivity of the developed model was evaluated. Then the update of the probability was done by changing the state of the nodes. According to the results, personal protective equipment, social distancing, technology, Training, lessons learning, geographical factors, and attention to sensitive groups are seven effective factors in the prevention and control of COVID-19. According to the output of the sensitivity analysis of the model, to prevent and reduce COVID-19, the priority in decision-making should be attention to social distancing. Personal protective equipment, Training, technology, learning from past events, attention to sensitive groups, and geographical factors are the next priorities respectively. The model developed using the Bayesian network can play an effective role in macro-decisions by prioritizing measures to prevent and reduce the spread of the COVID-19.

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