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Monitoring and Early Warning of SMEs' Shutdown Risk under the Impact of Global Pandemic Shock

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Abstract: The COVID-19 outbreak devastated business operations and the world economy, especially for small and medium-sized enterprises (SMEs). With limited capital, poorer risk tolerance, and difficulty in withstanding prolonged crises, SMEs are more vulnerable to pandemics and face a higher risk of shutdown. This research sought to establish a model response to shutdown risk by investigating two questions: How do you measure SMEs' shutdown risk due to pandemics? How do SMEs reduce shutdown risk? To the best of our knowledge, existing studies only analyzed the impact of the pandemic on SMEs through statistical surveys and trivial recommendations. Particularly, there is no case study focusing on an elaboration of SMEs' shutdown risk. We developed a model to reduce cognitive uncertainty and differences in opinion among experts on COVID-19. The model was built by integrating the improved Dempster's rule of combination and a Bayesian network, where the former is based on the method of weight assignment and matrix analysis. The model was first applied to a representative SME with basic characteristics for survival analysis during the pandemic. The results show that this SME has a probability of 79% on a lower risk of shutdown, 15% on a medium risk of shutdown, and 6% of high risk of shutdown. SMEs solving the capital chain problem and changing external conditions such as market demand are more difficult during a pandemic. Based on the counterfactual elaboration of the inferred results, the probability of occurrence of each risk factor was obtained by simulating the interventions. The most likely causal chain analysis based on counterfactual elaboration revealed that it is simpler to solve employee health problems. For the SMEs in the study, this approach can reduce the probability of being at high risk of shutdown by 16%. The results of the model are consistent with those identified by the SME respondents, which validates the model.

Keywords: DS evidence theory; Bayesian network; COVID-19; SME; Sensitivity analysis

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1. Introduction

According to the John Hopkins University COVID-19 Dashboard, as of 7 October 2022, the total number of infected people by COVID-19 has exceeded 620 million; the total number of deaths has exceeded over 6 million (6,554,597) and is still growing. The numbers are broken down by country as follows: China (infected count: 2,785,437; deaths: 15,432), United States (over 96 million; 1,062,130), India (over 44 million; 528,754), Brazil (over 34 million; 686,706), France (over 35 million; 156,409), Germany (over 33 million; 150,406), Korea (over 24 million; 28,614), United Kingdom (over 23 million; 208,256), and Italy (over 22 million; 177,356) [1]. Due to the mutation and evolution of COVID-19, several rounds of domestic and international outbreaks have been triggered since 2019. During this period, travel and migration of people were prohibited, and product manufacture and import and export trade were greatly affected. Overall, the uncertain situation was a challenge for SMEs.

SMEs play an important role in the development of a nation's economy, and a large number of jobs are created through employment with SMEs. Before COVID-19, Brazil had 6.4 million establishments, with 99 percent belonging to SMEs [2]. In Nigeria, approximately 96% of businesses are SMEs [3]. For Asia, SMEs are the backbone of the economy, accounting for 98% of all enterprises and 66% of the national labor force [4]. However, COVID-19 made many SMEs shut down, causing numerous workers to lose their jobs. In the following study, we will use an SME from the wholesale and retail trade as a case study. The SME has limited liquidity compared to larger enterprises. During the pandemic, SMEs could not operate normally because of lax management systems and the high number of infected employees who could not work properly. In contrast, large enterprises had stronger endurance and faster resilience.

At the end of 2019, the sudden global outbreak of COVID-19 forced many countries to implement preventive and control measures such as home quarantine and the shutdown of production in some enterprises; since then, against the backdrop of the aforementioned global pandemic shock, companies have continued to face the problem of shutdown and production suspension. The restaurant industry suffered such consequences first and bore the brunt of the consequences, with some restaurants even facing permanent closure, along with the travel, retail, hospitality, food services, entertainment services, and construction sectors. Due to their lower requirements for startup capital and labor, SMEs make up a larger portion of these industries when compared to large corporations. According to OECD, 60% to 70% of SMEs conduct business in these sectors [5], and SMEs have been hit the hardest by COVID-19; as a result, overcoming the shutdown risk caused by the pandemic has become a major challenge for many SMEs.

In the US, some enterprises have irregularly enforced lockdown orders since mid-March 2020, bringing the economy to a standstill. According to the Washington Post, more than 100,000 SMEs have permanently closed since the outbreak of the pandemic in early March 2020, accounting for 2% of the number of SMEs in the United States [6]. In accordance with the data from the International Labor Organization (ILO), the unemployment rate in the US in October 2020 was 6.9%, up 3.3% from October 2019, and it rose to 15% after a month [7]. As the COVID-19 pandemic eases, countries are lifting their lockdowns to revive global economic growth. However, as of May 2021, compared to January 2020, 34% of SMEs in the United States were closed [8].

Since January 2020, the Chinese government has implemented lockdown orders, causing more than 90% of Chinese enterprises to suspend work and production [9] for a period of time. The job market was also weak, with the jobless rate increasing from 5.3% in January to 6% in April [10]. As of March 2022, 1.262 million market entities were cancelled in China, an increase of 24.5% year-on-year, including 291,000 enterprises, 90,000 farmers' professional co-operatives, and 962,000 self-employed industrial and commercial households [11]. In the context of uncertainty about the development of the pandemic, in January 2022, confirmed cases of COVID-19 appeared in three workshops of the garment manufacturing department of the Shenzhou Company in Ningbo, Zhejiang Province, China, and the source of the virus is still unclear. According to the analysis and judgment of experts, the possibility of "items infecting people" cannot be ruled out. As a result of the outbreak, a part of the company's production bases have been closed, and production has been temporarily suspended.

In addition to the United States and China, SMEs in other countries have also been deeply affected by the pandemic. For example, in the first half of 2021, more than 70,000 companies in Vietnam closed down, with an average of about 400 companies closing down every day [12]. Clearly, some SMEs are at risk of shutdown at any time under the impact of the global pandemic shock. In particular, the source and mode of transmission of COVID-19 remain unknown and difficult to trace. Therefore, it is of great significance for the sustained and high-quality development of the global economy to explore SMEs' shutdown risk under the impact of a global pandemic and to carry out monitoring and early warning.

This paper presents the first evaluation method combining DS evidence theory and Bayesian networks applied to calculate SMEs' shutdown risk and constructs the evidence Bayesian network (DSBN) model. We integrate expert knowledge into algorithms and then use improved DS evidence theory to deal with uncertain information data. Then, the DSBN model is constructed through Bayesian structure learning, and the probability distribution of SMEs' shutdown risk is obtained by model parameter learning. The research framework of this paper is shown in Figure 1. We introduce experts' experience to construct an index system that incorporates factors related to the pandemic, employees, governments, and SMEs. Then, we adopt the DSBN model to simulate analysis of SMEs' shutdown risk. This model is used to carry out sensitivity analysis and causal inference to provide some management countermeasures and suggestions to SMEs, governments, and employees.

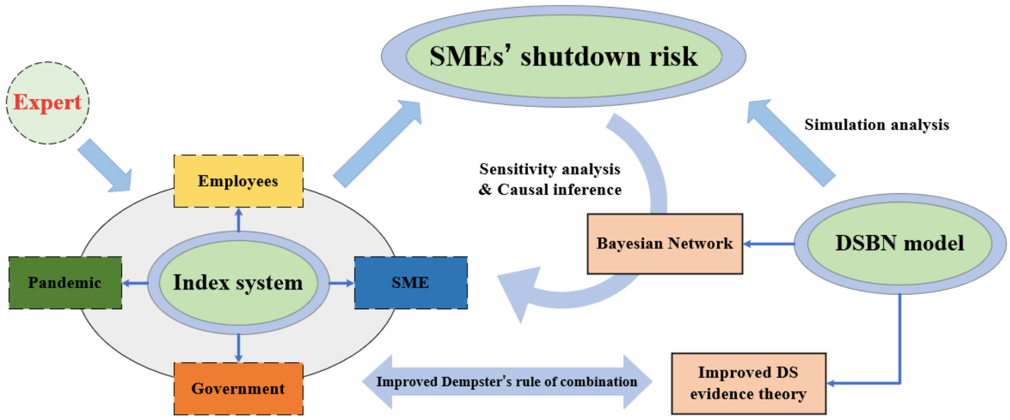

Figure 1. The research framework.

In data fusion, we used a modified Dempster's rule of combination based on weight assignment and matrix analysis (Section 3.1.1). For the methodology, five experts were invited to evaluate the metrics, which are divided into three levels. We performed risk monitoring using GeNIe 2.0 software, which is not only easy to operate for SMEs' employees but also allows real-time monitoring and early warning of SMEs' shutdown risk, visually identifying the key factors affecting the shutdown risk at each stage. GeNIe2.0 includes various functions of Bayesian network models, such as most likely causal chain analysis and sensitivity analysis. These functions enable SMEs and governments to undertake real-time monitoring and simulation analysis, provide early warning of unforeseen circumstances, and plan effective preventive steps ahead of time. This method may be implemented to scientifically monitor the shutdown risk for SMEs and provide additional reasonable pandemic prevention and control strategies.

While COVID-19 has a negative impact on SMEs, specific case studies of SMEs can further reveal different degrees of impact. We therefore set out to examine the factors of SMEs' shutdown risk and respond to two research questions: (1) How do you calculate SMEs' shutdown risk during a pandemic? (2) How do you reduce the negative impact of COVID-19 on SMEs?

2. Literature Review

Regarding monitoring SMEs' shutdown risk during the pandemic, the following literature review can be divided into four parts.

2.1. Current Situation of SMEs during the Pandemic

Scholars first explored the current situation of SMEs during the pandemic. Most SMEs shut down their work, resulting in difficulty in paying workers' wages [13]. Lu et al. [14] surveyed some SMEs in China. It was found that most SMEs were unable to resume work because of a shortage of pandemic mitigation materials, the inability of employees to return to work, disrupted supply chains, and reduced market demand. Zhang and Mao [15] took foreign trade enterprises as their main research objects and believed that the main difficulties under the pandemic concerned four aspects: declining demand, poor logistics, pressure on the capital chain, and blocked offline exhibitions. The above factors could be reviewed as the primary causes of SMEs' shutdown risk during the pandemic, which is a key reference for the building of a SMEs' shutdown risk assessment index system.

2.2. Factors Affecting Shutdown Risk

Some scholars used algorithms to identify SMEs' shutdown risk factors during the pandemic. Wang et al. [16] used daily operation data to conduct a fine-grained and multidimensional analysis of the operation status of SMEs and provided policy suggestions for their healthy development. Kuckertz [17] proposed a mixed method that combines a qualitative approach with quantitative analysis of international media. Startups can use this technique to quickly respond to the pandemic's effects. Tomasz et al. [18] used regression and machine learning tools based on travel company data. They showed that companies with low valuations, limited leverage, and high investments resisted pandemic-caused downturn better. Orcun et al. [19] proposed a new insolvency risk measure based on survey responses. They discovered that SME insolvency risk during the pandemic was significantly influenced by issues with finding customers and the cost of production and labor. We may create a rational and scientific SMEs' shutdown risk assessment index system for identifying risk variables by combining quantitative and qualitative methodologies.

2.3. Methods for Assessing Pandemic Risk Situation

Scholars believe that the main factors affecting the shutdown of SMEs can be attributed to the problems of logistics and demand caused by pandemic prevention and control measures. Effective pandemic prevention and control measures allow SMEs to reduce the risk associated with pandemics and, in turn, lower the shutdown risk. As a result, some scholars have explored the pandemic risk situation from the perspective of prevention and control. Chen, Chang, and Gong [20] proposed a set pair analysis method based on the Mahalanobis–Taguchi system (MTS) to measure enterprise pandemic prevention and control risk indicators. Pang and Zheng [21] took boarding schools as their research object and simulated the pandemic risk by presetting different levels of campus prevention and control. Yin and Zhang [22] proposed a three-party differential game model including factors such as the risk coefficient for virus infection and EP experience teaching. Then, prevention strategies, prevention efficiency, and prevention losses were compared under the three models based on theoretical analysis and numerical analysis. Huang and Kang [23] built the pandemic risk time series model to evaluate the effectiveness of COVID-19 control and prevention in different regions in China. Wang [24] researched the possibility of work resumption and the rating of pandemic prevention and control through kernel density estimation.

2.4. Methods for Risk Monitoring and Early Warning

The methods for risk monitoring and early warning research focus on various algorithmic models such as indicator systems [25–27], neural networks [28,29], Bayesian networks [30–32], support vector machines [33], and evidence theory [34–36]. However, outbreaks are often sudden, and the source of risk is affected by many uncertain factors. In recent years, the research trend on how to process uncertain information and knowledge fusion in the era of big data has become a hot spot [37]. Scholars have applied the method of combining evidence theory and a Bayesian network to the research of problems in different directions. Chen, Wang, and Li [38] used the method to predict the risk of road transport accidents with hazardous chemicals. C. Simon, P. Weber, and A. Evsukoff [39] used the method to compute complex system reliability. Li, Zhang, and Liu [40] used the method to assess marine disaster risk under the small sample condition. Wang, Cai, and Wei [41] used the method to assess the impact and damage of Natech accidents. Wang et al. [42] proposed a power grid fault location method via evidence theory and a Bayesian network. In the evidence theory, one usually adopts the form of expert scoring, and the expert scoring contains certain subjectivity and uncertainty. Scholars have used the Markov model and structural entropy weight method to quantify modeling or reduce the complexity of uncertain calculations [43,44]. Scholars have applied the evaluation method combining DS evidence theory and a Bayesian network in multi-domain problems and proved that the method can effectively deal with uncertain problems. We divided the pertinent studies on risk assessment problems into three aspects: scoring model, evaluation model, and DSBN model applications. For each aspect, we summarized common methods, references, and years of publication. The mind map for the risk assessment problems is shown in Figure 2.

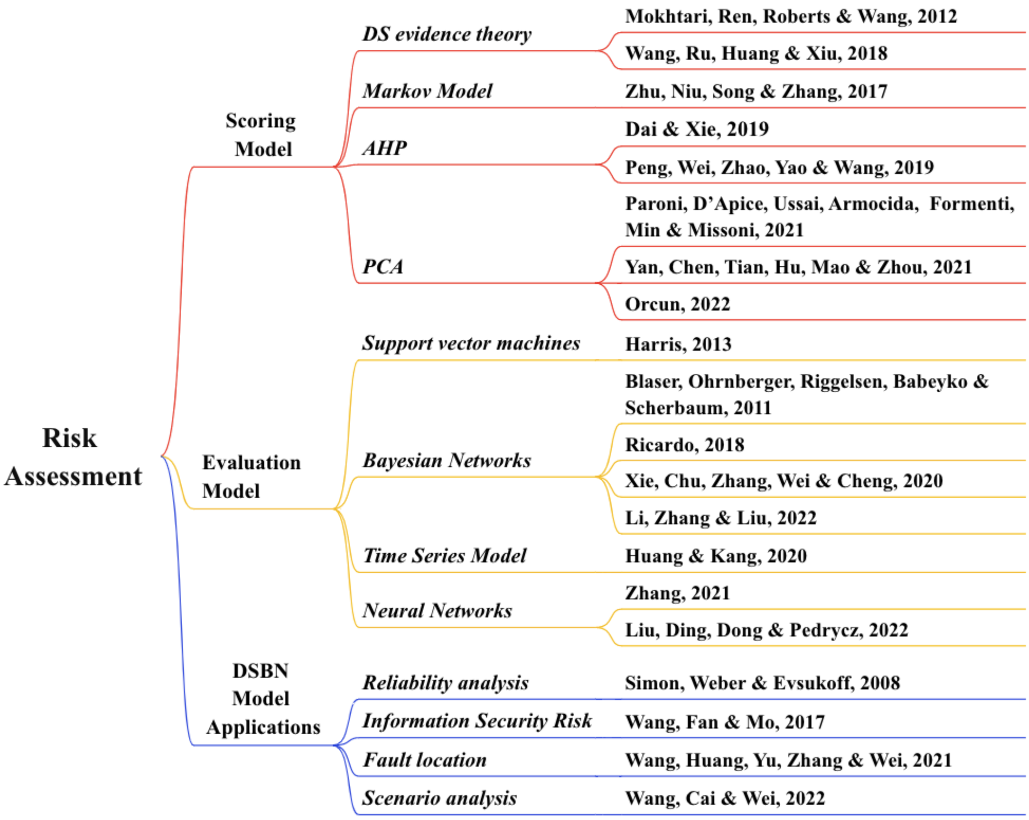

Figure 2. Mind map for the risk assessment problems [19,23,25–29,31–36,39–43,45,46].

3. Methodology

3.1. DSBN Model

This paper uses improved DS evidence theory for data fusion, a Bayesian network for causal inference, and builds a theoretical analysis model for SMEs' shutdown assessment (referred to as the DSBN model). The main theoretical explanations are as follows.

3.1.1. Improved DS Evidence Theory

Evidence theory, also known as the Dempster–Shafer evidence theory or DS evidence theory, is an approach to decision-making based on expert experience that can effectively deal with uncertainty. However, when there are conflicts or differences in the evaluation opinions given by expert experience, and the evaluation dimension of indicators is high, it will lead to certain uncertainty in decision-making, and the obtained results may not be ideal. Therefore, this paper introduces DS evidence theory, treats each expert's evaluation opinion as individual evidence, and corrects and fuses the conflicting evidence through an improved Dempster's rule of combination based on weight assignment and matrix analysis to make the expert's evaluation opinion more objective.

First of all, this paper expounds on the principle of DS evidence theory:

Let Θ denote a finite set of N deterministic objects, i.e., the identification framework $\Theta, \Theta = \{1, 2, \cdots, N\}$ and $P(\Theta)$, the power set of Θ, containing 2^{N} subsets of Θ. Let $m : P(\Theta) \to [0, 1]$ be a function satisfying $\sum_{A \subseteq \Theta} m(A) = 1$, the basic probability assignment function (mass function). Given n belief structures, $m_1, m_2, \cdots, m_n$ in DS evidence theory, the combination of n basic probability assignment structures is essential. There are different ways to fuse multiple yet conflicting sources of information. The level of conflict between these evidential sets is the basis for selecting an appropriate combination rule to use. Dempster's rule of combination is a technique to aggregate the belief masses assigned to focal sets by multiple independent databases or experts. The joint belief mass $m(A)$ can be calculated as [45]:

$$m(A) = \frac{\sum_{A_i \cap B_j \cap C_k \cap \cdots = A} m_1(A_i) m_2(B_j) m_3(C_k) \cdots}{1 - K}, A \neq \phi \ . \tag{1}$$

Second, based on DS evidence theory, we use the improved Dempster's rule of combination based on weight distribution to fuse the expert evaluation opinions. The improved synthesis formula is [45]:

$$m(A) = \sum_{A_i \cap B_j \cap C_k \cap \cdots = A} m_1(A_i) m_2(B_j) m_3(C_k) \cdots + f(A), A \neq \phi \ , \tag{2}$$

where $f(A) = K \times q(A)$ is a probability allocation function for evidence conflicts, assigning the degree of conflict between the evidence to each element in the matrix A. Therefore, this probability allocation function is satisfied $\sum_{A \subset \Theta} f(A) = K$. Let $q(A) = \frac{\sum_i^n m_i(A)}{n}$ assign K to A in this proportion.

According to [45], the improved Dempster's rule of combination is applied on the basis of matrix analysis. It is assumed that a total of n experts evaluate m indicators, and the steps are shown in Figure 3. First, convert the expert evaluation into matrix form, expressed as $Z_i = (a_{i1}, \cdots, a_{im}), i = 1, \cdots, \mathrm{n}$. Then, multiply the transpose of Z_1 with Z_2 to obtain the matrix $M(1)$. Next, multiply the column matrix formed by the main diagonal of $M(1)$ and Z_3 to obtain matrix $M(2)$, and repeat this step until all expert opinions are fused and matrix $M(n-1)$ is obtained. Finally, the probability value X_j is calculated for each $j = 1, \cdots, m$,

$$X_j = M(n-1)_{jj} + K \times \frac{\sum_{i=1}^n Z_{ij}}{n} \ . \tag{3}$$

In (3), $M(n-1)_{jj}$ is the element in row j and column j of $M(n-1)$; $\frac{\sum_{i=1}^n Z_{ij}}{n}$ represents the average degree of support of all evidence pairs, assigning the degree of conflict K to Z in this ratio. Among them, the calculation formula of the conflict degree K is as follows:

$$K = \sum_{i=1}^{n-1} \sum_{p \neq q} M(i)_{pq} \ldots \ p, q = 1, \cdots, m \ . \tag{4}$$

In this paper, through the above fusion method, the obtained expert evaluation results are used as the probability values of observable nodes in the DSBN model structure to provide data support for subsequent parameter learning.

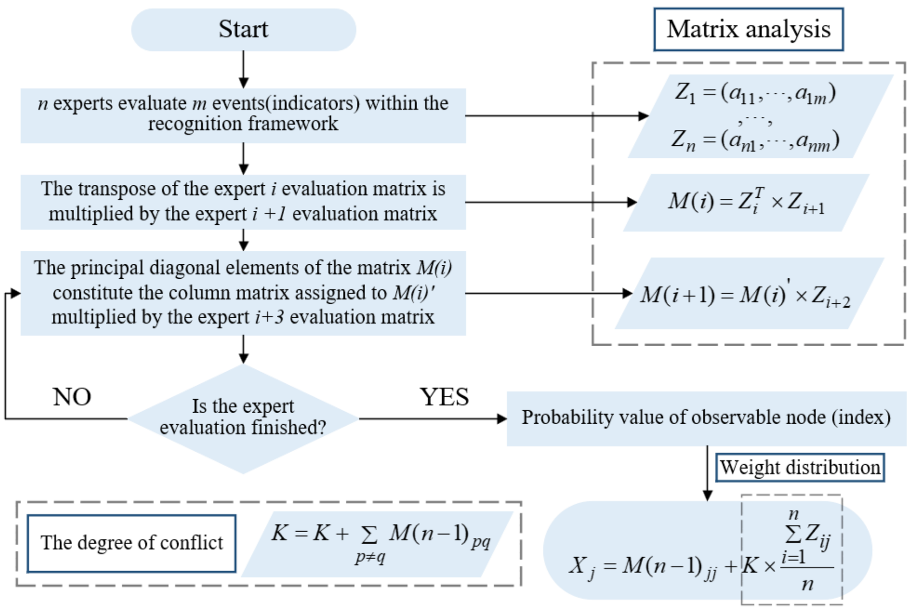

Figure 3. Flow chart of data fusion method based on improved DS evidence theory.

3.1.2. Bayesian Network

The Bayesian network (BN) is an extension of the Bayesian approach in mathematics. It belongs to a probabilistic graphical model. Within the field of uncertain knowledge representation and reasoning, BN theory is currently one of the most effective theoretical models.

According to [46], a directed acyclic graph is expressed as G, where $G=(V,E)$ denotes DAG, with n random variables denoted by $X=\{X_1,\cdots,X_n\}$. V represents the set of all nodes in the graph, and E is the set of directed edges. Associated with each node, X_i is a conditional probability distribution, which quantifies how much a node depends on its parents. The set of all parent nodes of a node X_i in G is denoted by $Pa(X_i)$, where the parent nodes describe the cause, and the child node shows the effect. The joint probability distribution of $(X_1,\cdots,X_n)$ is as follows:

$$p(X_1,\cdots,X_n)=\prod_{i=1}^{n}p(X_i|pa\,(X_i)). \tag{5}$$

Then, X is referred to as a Bayesian network of a directed acyclic graph G. Based on the BN theory, the method flow of constructing the BN model is shown in Figure 4.

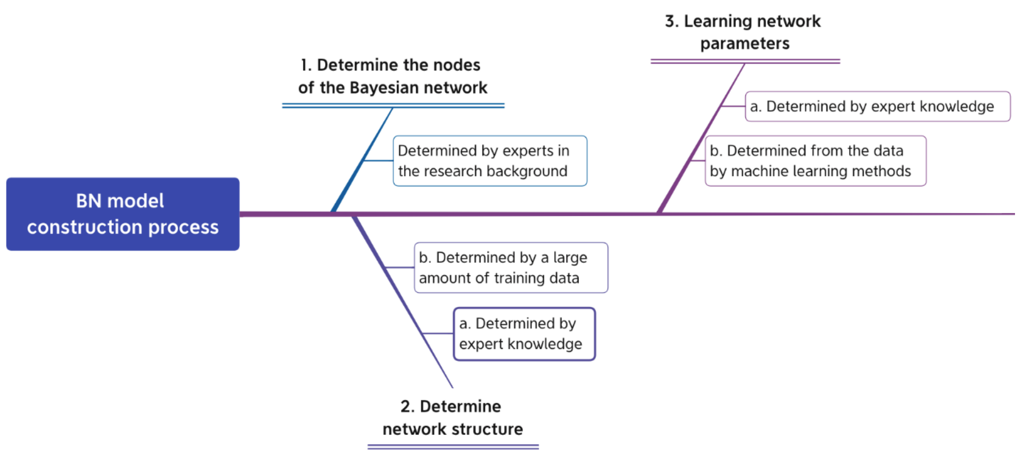

Figure 4. Flow chart of BN model construction method.

3.1.3. DSBN Model Construction

The construction process of the traditional Bayesian network model is shown in Figure 4, and its learning process can be divided into structure learning and parameter learning. The construction method of the DSBN model proposed in this paper involves two steps: first, experts in the research field select the nodes of the DSBN model. Then, the structure of the DSBN model is obtained through a large amount of training data, and the distribution parameters are determined by expert knowledge. The DSBN model differs from the traditional BN model in that parameter learning is performed by incorporating the improved DS evidence theory approach to eliminate the conflicting opinions of different experts, including an improved Dempster's rule of combination. Due to the sudden nature of COVID-19, the pathology of the virus is still under study at this stage. Therefore, there are certain differences in the evaluation opinions of different experts, and the knowledge related to the pandemic has certain uncertainty. The DSBN model can start from the initial evidence of uncertainty, and it uses the knowledge of uncertainty to infer the probability of SMEs' shutdown event occurrence when the knowledge of the pandemic is uncertain. The probability of an event has a certain degree of uncertainty but is reasonable. This model not only enhances the ability of the traditional Bayesian network model to deal with uncertain information but also highlights the fusion of uncertain information.

The DSBN model combines improved DS evidence theory with Bayesian networks. Its advantages are:

1. BN is widely thought of as an essentially numerical method, requiring "exact" numbers with a high "accuracy". However, in some more subjective risk assessments where precise data are lacking, combining it with DS evidence theory can better eliminate the influence of subjectivity and lack of precise data on the evaluation results;
2. The combination of DS evidence theory and Bayesian networks can improve the objectivity and intuitiveness of risk assessment results [45].

3.2. DSBN Model Application

3.2.1. Establishing an Index System

Based on the Guidelines for Pandemic Prevention and Control Measures for Resumption of Work and Production in Enterprises and Institutions issued by China in response to the Joint Prevention and Control Mechanism for COVID-19 [47] and the existing research base of previous authors [30], as well as the current state of SMEs, SMEs' shutdown risk was divided into four primary indicators of personal management, enterprise management, government management, and external conditions, which were further subdivided into 16 secondary indicators, following the principles of scientificity, systematicity, and operability. Finally, under the guidance of experts, we established a corresponding SMEs' shutdown risk assessment index system, as shown in Table 1.

Table 1. SMEs' shutdown risk assessment index system.

The Risk Classification	Risk Indicator (Node)	The Risk Cause
A Personal management	A1: Health QR code exception	The employee's health QR code is abnormal due to abnormal health, having traveled or contacted a person in a medium-risk or high-risk area.
	A2: Residence controls	The place where the employees live is divided into a control area due to the pandemic.
	A3: Daily prevention and control is not in place	Employees have weak self-protection awareness. Employees wear masks and other protective equipment unconsciously in public places. Employees do not cooperate with prevention and control, etc.

Table 1. *Cont.*

The Risk Classification	Risk Indicator (Node)	The Risk Cause
B Enterprise Management	B1: Lack of strict management of incoming and outgoing personnel	SMEs do not strictly manage all channels in and out of the enterprise. SMEs do not strictly review information registration, temperature detection, and traffic trajectories of external personnel.
	B2: Inadequate prevention and control measures in the workplace	There is no special person responsible for the regular disinfection of public areas and items of work and life. There is no garbage classification management in public areas, no timely removal of garbage, and no timely disinfection of garbage bins.
	B3: Lack of strict dietary health management	The canteen purchases live poultry and fish that have not been slaughtered and quarantined. The daily inspection of the canteen is not in place.
	B4: Insufficient stockpiling supplies for pandemic prevention	The necessary medical supplies of the enterprise are insufficiently prepared. SMEs do not cooperate with disease control departments to standardize quarantine observation and tracking management.
	B5: The pandemic special contingency plan is not perfect	SMEs have not established an organizational system for pandemic prevention and control, emergency measures, and disposal procedures. SMEs did not implement the responsibility for prevention and control to departments and individuals. When employees developed suspicious symptoms, SMEs did not take timely isolation and disinfection measures.
	B6: Broken capital chain	SMEs have problems such as financing difficulties due to borrowing needs.
	B7: Home office mode	SMEs adopt online modes such as home offices to carry out work.
C Government Management	C1: Inadequate government supervision and management	Government regulators have not strictly reviewed SMEs' work resumption procedures and emergency plans.
	C2: Inadequate traffic management	Government departments are not strict with transportation pandemic prevention and safety management. The government failed to fully restore passenger routes under normalized prevention and control.
D External conditions	D1: SMEs are located in areas with increased risk of pandemic	The increased risk of the pandemic in the region where the SMEs are located will increase the risk of infection for the SMEs' personnel.
	D2: Market demand has shrunk	Market demand has shrunk to a certain extent due to the current pandemic situation.
	D3: Poor logistics	Traffic is under control due to the pandemic. Logistics has been affected by the pandemic.
	D4: Pandemic control in the region where SMEs are located	The location of the SMEs' office has been affected by the pandemic and has been designated as a control area.

3.2.2. SMEs' Shutdown Risk: DSBN Model

When assessing SMEs' shutdown risk, we first identify the risks faced by SMEs under the impact of a global pandemic, that is, as an observable node in the DSBN model. This paper takes the 16 risk indicators in the index system as nodes in the DSBN model. Then, we obtain the DSBN model of SMEs' shutdown risk shown in Figure 5 with the help of GeNle2.0

according to the opinions of experts. In the DSBN model, we regard SMEs' shutdown risk as a function of individual management, enterprise management, government management, and the external environment. The DSBN model performs parameter learning on the causal nodes of each node under the condition of prior probability and determines the strength of interdependence among the nodes.

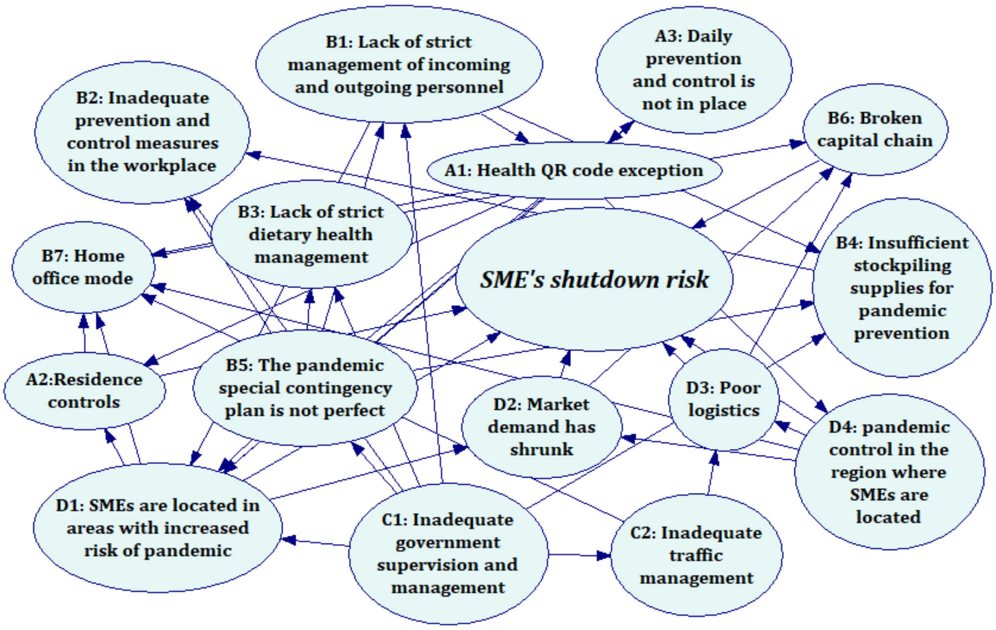

Figure 5. SMEs' shutdown risk DSBN model.

4. Result

4.1. SMEs' Shutdown Risk DSBN Model

Taking the scoring data assigned by five experts in the field of pandemic prevention and control and risk management as an example, this section will analyze the risk sources of SME shutdowns. We invited five experts to conduct a comprehensive evaluation of the 16 SMEs' shutdown risk factors in the risk assessment index system (described in Section 3.2.1, Table 1). Experts gave the probabilities of the risk factors at three levels: low risk (R1), medium risk (R2), and high risk (R3). Some evaluation results are shown in Table 2.

Table 2. Evaluation results of experts on risk factor A1.

Risk Factors A1	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Low Risk (R1)	0.4	0.3	0.2	0.6	0.5
Medium Risk (R2)	0.3	0.4	0.5	0.3	0.3
High Risk (R3)	0.3	0.3	0.3	0.1	0.2

The evaluation results in Table 2 were then calculated using the improved fusion method (according to Section 3.1.1, Equation (3)) in DS evidence theory, developed through matrix analysis (described in Equation (6)) and weight assignment (described in Equation (7)). Then, the steps in the flow chart of the data fusion method (described in Section 3.1.1, Figure 3) were applied to obtain the expert score data after data fusion of the influencing factors, as shown in Table 3.

$$M(4) = \begin{bmatrix} 0.4 \times 0.3 \times 0.2 \times 0.6 \times 0.5 & 0.4 \times 0.3 \times 0.2 \times 0.6 \times 0.3 & 0.4 \times 0.3 \times 0.2 \times 0.6 \times 0.2 \\ 0.3 \times 0.4 \times 0.5 \times 0.3 \times 0.2 & 0.3 \times 0.4 \times 0.5 \times 0.3 \times 0.3 & 0.3 \times 0.4 \times 0.5 \times 0.3 \times 0.2 \\ 0.3 \times 0.3 \times 0.3 \times 0.1 \times 0.5 & 0.3 \times 0.3 \times 0.3 \times 0.1 \times 0.3 & 0.3 \times 0.3 \times 0.3 \times 0.1 \times 0.2 \end{bmatrix} = \begin{bmatrix} 0.0072 & 0.00432 & 0.00288 \\ 0.009 & 0.0054 & 0.0036 \\ 0.00135 & 0.00081 & 0.00054 \end{bmatrix}. \quad (6)$$

$$\text{The result of risk factor A1 data fusion} = \begin{cases} X1 = 0.0072 + K \times \frac{0.4+0.3+0.2+0.6+0.5}{5} = 0.401944 \\ X2 = 0.0054 + K \times \frac{0.3+0.4+0.5+0.3+0.3}{5} = 0.3606696 \\ X3 = 0.00054 + K \times \frac{0.3+0.3+0.3+0.1+0.2}{5} = 0.2373864 \end{cases}. \quad (7)$$

$$K = \sum_{i=1}^{4} \sum_{p \neq q} M(i)_{pq} = \begin{bmatrix} 0.4 \times 0.4 & 0.4 \times 0.3 \\ 0.3 \times 0.3 & 0.3 \times 0.3 \\ 0.3 \times 0.4 & 0.3 \times 0.3 \end{bmatrix} + \begin{bmatrix} 0.4 \times 0.3 \times 0.50.4 \times 0.3 \times 0.3 \\ 0.3 \times 0.4 \times 0.20.3 \times 0.4 \times 0.3 \\ 0.3 \times 0.3 \times 0.20.3 \times 0.3 \times 0.5 \end{bmatrix} + \cdots + \begin{bmatrix} 0.00432 & 0.00288 \\ 0.009 & 0.0036 \\ 0.00135 & 0.00081 \end{bmatrix} \approx 0.98686\,. \quad (8)$$

Table 3. The result of risk factor A1 data fusion.

Risk Factors	R1	R2	R3
A1	0.401944	0.3606696	0.2373864

The above process was repeated for all influencing factors, and then the evaluation results of 16 influencing factors were obtained after data fusion through improved DS evidence theory. Further, Python was used to visualize the data and obtain the predicted value of the risk probability, as shown in Figure 6, in preparation for the DSBN model simulation analysis.

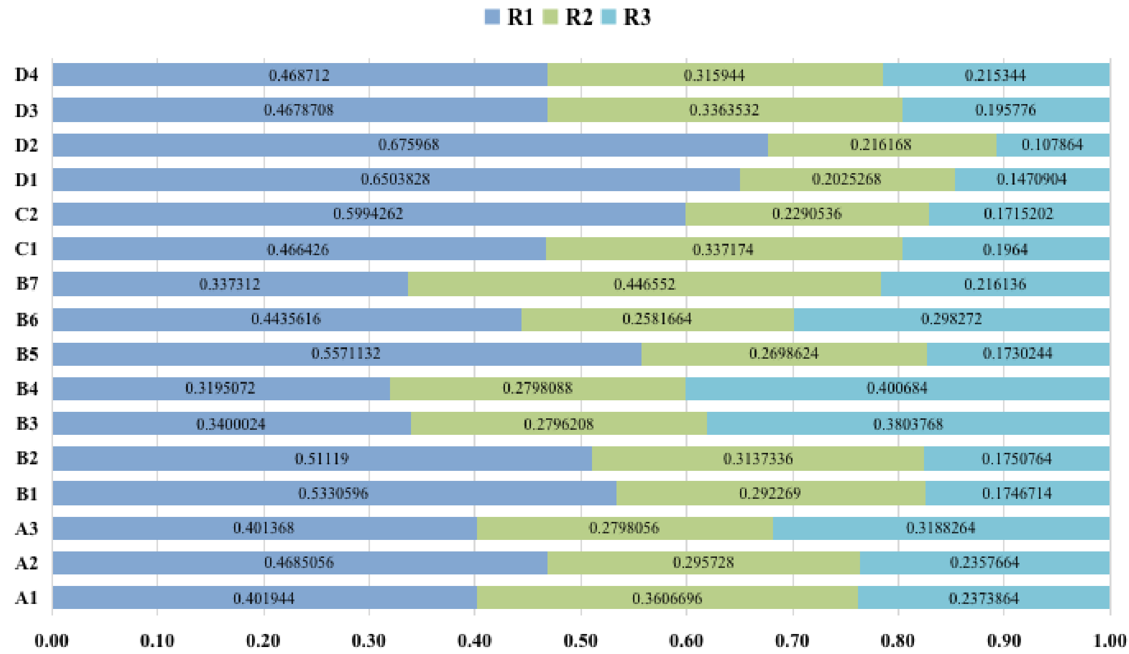

Figure 6. DSBN predicted value of risk probability.

4.2. Reasoning Results

In the DSBN model, the expert scoring result after data fusion is set as the corresponding state of the risk node. In GeNle2.0, the evaluation result obtained by SMEs' shutdown risk DSBN model after parameter learning is shown in Figure 7. The DSBN model uses the expert scoring result after data fusion based on the improved DS evidence theory (according to Section 3.1.1, Figure 3) as the probability value of the observation node. Through the DSBN inference learning results shown in Figure 7, it can be estimated that the probability of SME's shutdown risk being at low risk is 79%, and the probabilities of being at medium and high risk are 15% and 6%, respectively. It is also seen that the probability of SMEs' 16 risk factors being at a low-risk level is relatively high. This shows that the experts assessed that SMEs' pandemic prevention and control effect and business status are good, and the risk probability of SME's shutdown at this time is low.

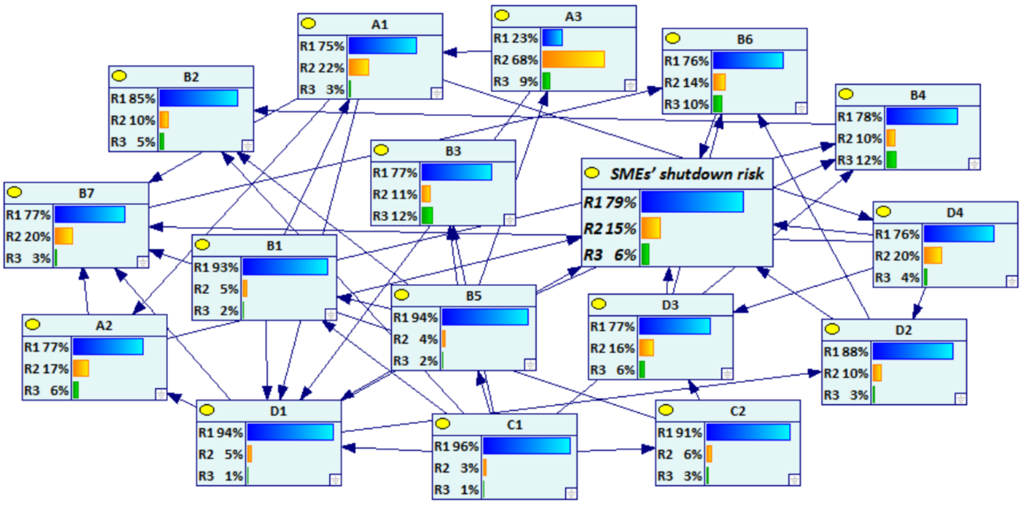

Figure 7. DSBN inference learning results.

4.3. Sensitivity Analysis

To measure the degree of influence of a small change in a factor on the target object, sensitivity analysis was performed. Usually, when the sensitivity value is higher, the impact of the factor indicator on the target object is greater, and there will be more serious consequences. GeNle2.0 visualization software was used to calculate the sensitivity value of each node, as shown in Figure 8.

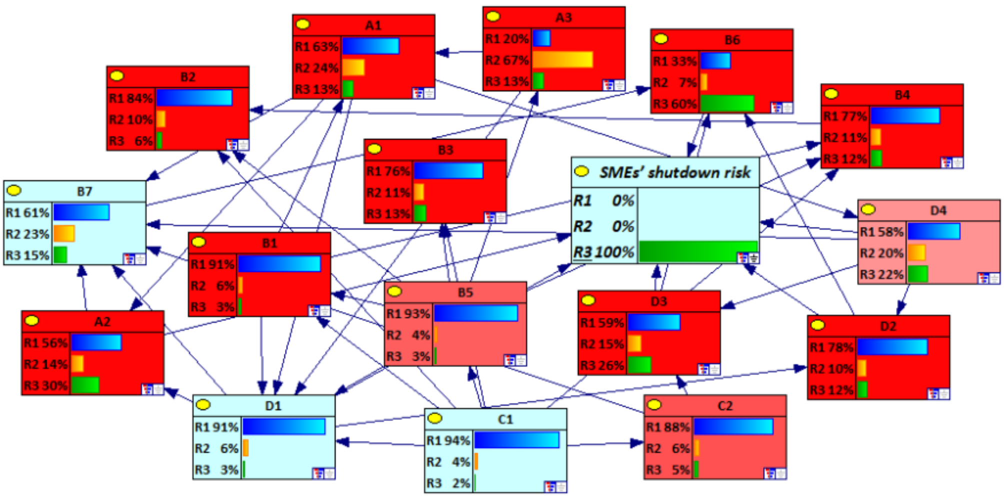

Figure 8. Sensitivity analysis results.

The darker the color of the node in Figure 8, the more sensitive the node is, and the greater the impact it has on assessing SMEs' shutdown risk. From the sensitivity analysis results, the darkest nodes are *health QR code exception* (A1), *residence controls* (A2), *daily prevention and control is not in place* (A3), *lack of strict management of incoming and outgoing personnel* (B1), *inadequate prevention and control measures in the workplace* (B2), *lack of strict dietary health management* (B3), *insufficient stockpiling supplies for pandemic prevention* (B4), *broken capital chain* (B6), *market demand has shrunk* (D2), and *poor logistics* (D3). To avoid the high-risk state of shutdown, SMEs should pay attention to their healthy operations first. In the process of normalizing pandemic prevention and control, they need to carry out close surveillance to strictly manage the health and travel of employees and implement pandemic prevention and control measures. Under the impact of the pandemic, SMEs should seize policy opportunities, rationally adjust the operation mode of SMEs, and reduce the impact of capital chain, market demand, and logistics problems caused by the pandemic. The lighter-colored nodes in Figure 8 are *the pandemic special contingency plan is not perfect* (B5), *inadequate traffic management* (C2), and *pandemic control in the region where SMEs are located* (D4). It can be seen that SMEs should also make special response plans for the pandemic. Government departments should strengthen measures in traffic management in a timely manner. In this way, the shutdown risk caused by pandemic control in the area where SMEs are located can be lowered.

4.4. The Most Likely Causal Chain of SMEs' Shutdown

We assumed that this SME experienced a shutdown event, i.e., it faced a maximum risk of a shutdown in the DSBN model. Setting the probability of this SME's shutdown risk "R3" at 100%, the most likely causal chain (according to Figure 9) was: *Inadequate government supervision and management* (C1) → *The pandemic special contingency plan is not perfect* (B5) → *Daily prevention and control is not in place* (A3) → *Health QR code exception* (A1) → *Pandemic control in the region where SMEs are located* (D4) → *Market demand has shrunk* (D2) → *Broken capital chain* (B6) → *SME's shutdown risk.*

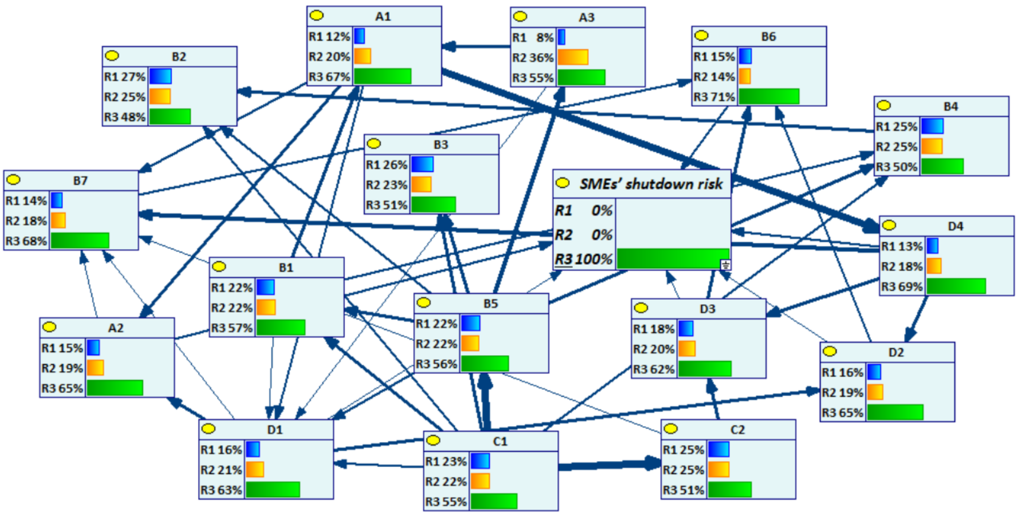

Figure 9. The most likely causal chain of SMEs' shutdown.

In fact, the probability of high shutdown risk for this SME we surveyed was 6%. Based on this prediction, we intervened in the target historical event in the counterfactual world (assuming SMEs' shutdown high risk is 100%) and gauged the causality between events by observing changes in known events. In the counterfactual analysis, proactive intervention was performed on the indicators in the most likely causal chain. What happens to the likelihood of higher shutdown risk if an indicator's high-risk status reaches 0%? This will be explained in Table 4 and its succeeding paragraph.

Table 4 displays the change in the likelihood that this SME is at high risk by eliminating all arrows in the DSBN model that flow into a particular indicator, setting the likelihood of it being at high risk to zero, and then computing the counterfactual outcomes. When the high-risk probability of interventions B6, D4, and D2 is 0%, the reduction in the probability of high risk of SMEs shutting down is relatively large, 33%, 29%, and 28%, respectively. However, when the effectiveness of mitigating the risks of these three problems is low, solving the A1 problem can alleviate and reduce the high risk of enterprise shutdown. At this time, the probability of being at a high risk of shutdown is 84%, a 16% reduction.

Table 4. The result of counterfactual analysis in the most likely causal chain of SMEs' shutdown.

P (SME's Shutdown Risk = R3)	P (C1 = R3)	P (B5 = R3)	P (A3 = R3)	P (A1 = R3)	P (D4 = R3)	P (D2 = R3)	P (B6 = R3)
94%	0%	88%	89%	99%	99%	94%	94%
94%	91%	0%	29%	98%	98%	93%	94%
95%	92%	49%	0%	98%	98%	94%	94%
84%	92%	50%	20%	0%	68%	90%	92%
71%	94%	48%	19%	65%	0%	82%	90%
72%	92%	47%	19%	62%	59%	0%	83%
67%	98%	98%	94%	99%	98%	93%	0%
100%	55%	56%	55%	67%	69%	65%	69%

It can be seen that the break of the capital chain is the main reason for SMEs' shutdown. However, the main factor causing the capital chain problem is that several pandemic control measures adopted by the government and SMEs due to insufficient supervision have affected the operation of SMEs in logistics, market demand, capital chain, and other aspects under the impact of the global pandemic. Therefore, we monitored SMEs' shutdown risk and put the above-mentioned risk factors on the most likely causal chain as the first priority for management and control based on the results of the early warning. In this way, SMEs can timely warn and adjust the operation mode while doing a good job in pandemic prevention and control, thereby reducing SMEs' shutdown risk and avoiding corresponding economic losses.

5. Discussion

Based on improved DS evidence theory and the Bayesian network, this paper constructed a DSBN model to assess SMEs' shutdown risk under a global pandemic. The DSBN model can be implemented to effectively assess SMEs' shutdown risk, as well as to identify the key influential factors by reasoning results, performing sensitivity analysis, and conducting causal inference on the most likely causal chain. This provides countermeasures for SMEs, the government, and employees.

Generally, SMEs are less able to survive a pandemic than larger enterprises. Large enterprises have relatively solid digital management platforms, while SMEs are very weak in this regard. In the course of this research, we found that SMEs are struggling to maintain their day-to-day operations and to afford the development of digital systems during the global pandemic. The DSBN model proposed in this paper is a kind of digital system for monitoring and early warning of SMEs' shutdown risk. The DSBN model application platform is GeNIe2.0, which is an easy-to-use and free open-source software that facilitates SMEs to use the monitoring platform for shutdown risk assessment at a low cost. The proportion of highly educated personnel in SMEs is relatively low, and the DSBN model is easier to understand than model algorithms such as neural networks [28,29].

We thoroughly evaluated the impact of some pandemic prevention and control measures when developing the SMEs' shutdown risk assessment index system. Unduly tight pandemic prevention and control measures can cause SMEs to fail to carry out their daily operations, while unduly lax prevention and control measures can contribute to the spread of pandemics. To some extent, assessing SMEs' shutdown risk can control the degree of implementation of pandemic preventive and control measures by SMEs and the government, facilitating the smooth operation of SMEs while controlling the pandemic and promoting the stable development of the national economy.

In risk studies that mostly use assessment methods, what kind of data is used for conducting a risk assessment is a question that most scholars think about. Data that are too subjective will seriously affect the scientificity and objectivity of the assessment results. Compared to simple descriptive statistics analysis [7,14], data using questionnaires to study the impact of COVID-19 on Chinese SMEs are based on subjective self-assessment, but we use an improved DS evidence theory to eliminate this subjectivity affected by individual preferences and perceptions, which improves the reliability of the questionnaire data to some extent. However, relative to evaluation methods such as social network analysis [25], this paper lacks objectivity in constructing a Bayesian network structure, and the constructed DSBN model is not comprehensive enough. In terms of the model network structure, we will try to use different machine learning algorithms for the Bayesian network structure learning in the future to enhance the scientific nature of the Bayesian network structure.

6. Policies of SMEs' Shutdown

Numerous effective policies are suggested in light of the widespread COVID-19 pandemic. The US government launched The Paycheck Protection Program (PPP) which began on 3 April 2020. PPP, as part of the CARES Act as a temporary source of liquidity for SMEs, authorizes USD 349 billion in forgivable loans to help SMEs pay their employees and additional fixed expenses during the COVID-19 pandemic [48]. The Chinese government added CNY 1.6 trillion in new loans to increase support for SMEs temporarily experiencing production and business difficulties due to the pandemic [49]. To help SMEs with their cash, the European Investment Bank will invest EUR 40 billion [7]. The preferential and subsidy policies of the government significantly aid SMEs in surviving the pandemic.

Based on the simulation analysis results, this paper makes the following recommendations for SMEs, governments, and employees to respond to shutdown risk during the pandemic. As for SMEs employees, the most important thing is to ensure their own health, carry out daily health monitoring, and conduct regular nucleic acid testing to avoid increasing SMEs' shutdown risk.

As for SMEs, they can first implement digital preventative techniques to combat the shutdown risk. SMEs can use the intelligent supervisory platform to control employees' work, health, and activity trajectories as well as to buy, distribute, and manage relevant medical supplies online. Second, SMEs are suggested to adopt diverse support techniques to reduce the shutdown risk. SMEs can develop one-to-one partnerships with large enterprises through the Chamber of Commerce, or they can look for diversified funding through a variety of channels, including government subsidies, inclusive banking, offshore banking or corporate finance, and collaborative support from banks and core enterprises. Finally, SMEs are encouraged to build diverse innovation systems to reduce the shutdown risk, innovate in the direction of digitalization and technology for products and technologies, diversify industries with the actual situation and global background, and boost marketing exploration and business models.

As for governments, they can provide a digital shared lending platform for SMEs to facilitate SMEs to find a compliant loan channel for their risk profile and complete loan applications through an integrated online platform to reduce population movement during the pandemic. Second, the government can provide certain employment subsidies for SME employees who are quarantined at home and temporarily stop working because of the pandemic. Finally, the government should do a good job of regulating the prevention and control of the pandemic to ensure efficient and smooth transportation.

7. Conclusions

This paper developed a risk assessment approach based on the improved DS evidence theory and Bayesian network for estimating reliable risk probabilities from experts' scoring data. In this study, we used improved DS methods to eliminate the variability of experts' scoring data. Examples were used to confirm that the improved Dempster's rule of combination significantly reduces the computing time and yields fused data that objectively synthesizes the experience of multiple experts. Furthermore, our work shows that this improved DS method is better for quantifying some qualitative indicators. Specifically, many uncertainty problems in the risk assessment domain are difficult to quantify, which makes risk assessment potentially challenging. Such uncertainty problems contain cognitive uncertainty and uncertainty about future trends. The solution to these problems adds an operational and widely used risk assessment model to the risk assessment domain. This model was developed from an improved DS method and Bayesian network inference.

Under the influence of the global COVID-19 pandemic, many SMEs are not strong enough to avoid closure or bankruptcy. They constitute a specific group of businesses, and risk management is especially important because smaller businesses are more frequently threatened by shutdown. Effective threat prediction and mitigation are helpful for reducing or even eliminating undesirable business phenomena and events. We proposed an approach to identify key risk factors for SMEs through sensitivity analysis of the DSBN model. Enterprise workplace management is not strict, and capital chain rupture and inadequate medical services are the key risk factors most threatening to the activities of SMEs. These factors indicate the main direction of risk management system planning and organization in the SME sector. The risk management department of SMEs can set up some reasonable regulations to reduce risks by addressing the identified key risk factors. We proposed approaches to identify some external influences, such as capital chain problems, through the most likely causal chain analysis based on counterfactual elaboration. It is a challenge to quickly manage some external risks and handle the capital chain problem during the pandemic. At this time, SMEs can reduce shutdown risk by strictly managing employee health issues. Therefore, SMEs can set up a risk assessment team in the risk management process and develop risk scoring criteria through expert discussions. The risk assessment team will carry out the daily risk assessment, and the scoring data will be trained by our proposed approach to monitor SMEs' shutdown risk.

This study has some limitations, notwithstanding the theoretical and practical consequences that were previously discussed. First, although we based our evaluations on the professional experience of experts, there were still improvements in data reliability. In further research, we need to improve the weight of data fusion and apply the result better in the DSBN model. Second, these findings are time-limited and may not apply to cities of all sizes. Future studies on the status of SMEs in the international setting should be examined to build a universal risk assessment index system that can be useful to compare and analyze risk trends of SMEs' shutdown risk across nations and investigate the potential reasons. Furthermore, it is anticipated that future research will use a larger sample size and will need to consider the use of some big data techniques. Last, this study looked at the entire industry, and conclusions were not suggested based on particular industry traits. Future research can therefore examine how COVID-19 has affected SMEs in a particular industry. For example, we can investigate the factors influencing SMEs' shutdown risk in several specific industries, construct corresponding DSBN models, and compare the variability across industries. These extensional directions will allow for a more in-depth discussion and enhancement of this study.

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