Risk analysis in the management of a green supply chain

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Risk analysis in green supply chain management for strategic decision-making within the framework of environmental and anti-consumption behavior

Article Running Head: **Risk analysis in green supply chain management**

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One Sentence Summary

A study to identify the risk factors associated with the processes involved in green supply chain management.

ABSTRACT

The objective of the research study is to identify the risk factors associated with the processes involved in green supply chain management. Grey relation analysis method was used to analyze the degree of connection between supply chain risk factors and key risk factors. Back Propagation Artificial Neural Network method was consequently used to determine the risk level associated with a green supply chain. The determination of risk level will help companies to develop effective strategic management initiatives in a green supply chain environment.

JEL CLASSIFICATION: C45

INTRODUCTION

Supply chain management (SCM) is a management approach that focuses on developing processes to improve the overall supply chain performance. SCM enables a company to create and maintain supplier management and collaboration strategies. Managers can explore ways of exploiting distribution channels, combined with the development of new information network technologies, to reduce distribution costs in in order to improve the profitability of various product channels. As stressed by Christopher (2016), competition is characterized less about rivalries between companies but more between supply chains. This phenomenon demonstrates the importance of supply chains, and effective SCM, in modern enterprises.

The impact of the supply chain on the environment has been well documented. For example, McKinsey & Co (2016) reported that the typical consumer company’s supply chain accounts for more than 80 percent of greenhouse-gas emissions and more than 90 percent of the impact on air, land, water, biodiversity, and geological resources. It is therefore argued that environmental management should be employed at every stage of the supply chain (Nagel, 2000). This school of thought gives rise to green supply chain management (GSCM), which is essentially the combination of SCM and environmental management.

The concept of GSCM is consistent with the increasing global trend for goods and services to conform to the standards for sustainable trade practices. GSCM enables companies to meet increasing consumer demand for sustainable products. At the same time, through the reduction of material costs and operating costs, GSCM can enhance the competitiveness of companies, giving them a strategic advantage over challengers operating in the same market (Zhao & Ai, 2018).

However, GSCM often entails dealing with many unpredictable factors in its processes, which can affect upstream and downstream components in a supply chain. As a consequence, risk management in GSCM is significant. First, it can help managers to assess and evaluate the level of risk associated with a green supply chain (GSC), thus allowing companies to adopt preventive measures due to uncertainty in a supply chain (Xi, 2011). Second, consumers can be made aware of the adoption of sustainable practices applied to the inputs used by a GSC such as low energy use and lower carbon emissions. Awareness is of particular relevance for ethical consumers who are willing to reward or punish companies for their sustainable performance (Moisander, 2007; Young et al., 2010, Shaw & Newholm, 2002)

There is evidence to suggest that GSCM can have an impact on anti-consumption i.e. to promote the practice of reducing or even eliminating consumption (Peattie & Peattie, 2009). Lee et al. (2009) argue the concept of anti-consumption does not necessarily have to result in diminished business performance. Anti-consumption tries to replace classical consumption with more environmentally friendly ways to achieve the same desired output, and advocates for the principle of low-carbon consumption. As a result, it can be considered that GSCM and anti-consumption have similar objectives（Ji & Li, 2015).

Researchers have traditionally focused mainly on the relationship between GSCM practices and the environment, economy or performance. Surprisingly, there is a paucity of research on the risk criteria affecting GSCM practice. Many uncertainty factors in the operation process of a GSC will affect the components of the production chain. Furthermore, the determination of risk indicators, which is the basis of risk identification, is of significance (Mangla et al., 2015). As a result, this study will investigate the determination of risk levels in GSCM and will provide guidelines for managers to make timely adjustment decisions in order to reduce risk.

LITERATURE REVIEW

Green supply chain management

The concept of a GSC was first introduced in an environmentally responsible manufacturing study (Handfield, 1996). The notion of a GSC means that principles of environmental management should be integrated into the whole supply chain process in order to maximize the use of resources and minimize any resulting environmental impact (Walton et al., 1998). Incorporating environmental issues into SCM practices is known as green supply chain management (GSCM) (Kenneth et al., 2012).

There is however no universal definition of GSCM which is also referred to as supply chain environmental management (Lippmann, 1999; Darnall et al., 2008; Ali, 2020), green supply (Yildiz, 2019), green logistics and environmental logistics (Nihan, 2011), green procurement (Wang, 2019), reverse logistics (Hu & Jia, 2020) or as a series of strategies and methods adopted in the process of SCM to integrate the concept of environmental protection to achieve sustainable goals. It is also argued that GSCM is a collective capability that combines four different but interrelated sets of practices: environmental management systems, ecological design, resource reduction and external environmental practices (Al-Sheyadi & Muyldermans, 2019).

For managers, the implementation of GSCM is conducive to competitive advantage. For instance, it can enable a company to establish a positive corporate image in order to win customers' trust. GSCM can also benefit from significant cost efficiencies. The use of fewer resources and more efficient logistics modes associated with green logistics can reduce operating costs and increase company profits (Zhang, 2012). It can also help enterprises bypass existing barriers to green operations and take advantage of international markets.

Laosirihongthong & Adebanjo (2013) analyzed the impact of GSCM on the environmental, economic and intangible performance of companies. Similarly, the general relationship between specific GSCM practices and environmental and economic performance was evaluated (Zhu, 2004). Lin (2013) investigated the three main influencing factors of GSCM principles: practice, performance and external pressure from stakeholders. Ninlawan (2010) analyzed eleven manufacturers in terms of their green sourcing, green manufacturing, green distribution and/or reverse logistics activities. In another study, significant positive correlations were found between organizational learning mechanisms, organizational support, and adoption of GSCM practices (Zhu, 2008).

A review of the literature indicates that the existing GSCM research is comprised mainly of studies whose exploratory methods are predominantly qualitative. This research study combines qualitative and quantitative methods in order to explore the relevant risk factors that exist in GSCM.

Risk criteria and methods in GSCM

An important area of study is the risk criteria affecting GSCM practices. Behzadi (2018) conducted a comprehensive review of the relevant literature on quantitative risk management modelling of agricultural supply chains, taking into consideration the robustness and elasticity of key factors for risk management. The use of material performance analysis (IPA) methods have also been shown to provide strategic recommendations with regerad to improving the performance of manufacturing supply chains (Shenoi, 2018). A framework for sustainable supply chain risk management assessment has also been established (Rostamzadeh et al., 2018). Wang (2018) followed the approach of analysing risk factors affecting a supply chain acording to external factors, internal factors and overall factors. External factors were further divided into political factors, economic factors, natural factors, legal factors and consumption factors, while internal factors were expanded to take into account business decision-making, management control and risks associated with logistics operations. The category of overall factors was categorised according to the risk related to the pursuit of profit targets, supply chain contract risk, supply chain information system risk and supply chain capital flow risk.

The determination of the level of risk in a supply chain is of significance with regard to the successful implementation of a GSC, which includes the establishment of risk evaluation criteria and the construction of a risk evaluation model.

In terms of the selection criteria for determining risk, researchers put forward different computational evaluation methods, including objective analysis methods (Moradi et al., 2019), quantitative combination of Gini coefficient - partial correlation analysis (Meng & Chi, 2016), rough set, analytic network process (ANP) (Ahmadizadeh-Tourzani, 2018), analytical hierarchy process (AHP) and the technique for order of preference by similarity to ideal solution (TOPSIS) (Jain et al., 2018), as well as decision making trial and evaluation laboratory (DEMATEL) tests and evaluation tests (Lin, 2018).

However, there are several shortcomings in the practical application of these methods. For example, the identified principal components being investigated have poor generality, and the resulting data are often difficult to interpret (Konishi & Tomokazu, 2015). Although AHP is widely used, it is difficult to achieve satisfactory results with regard to consistency tests when there are a large number of factors. DEMATEL, though practical, ignores the relationship of factors (Tamura, 2005). In contrast, grey correlation analysis (Wang et al., 2017) can select key factors and indicate the degree of correlation between factors and targets.

Common methods employed for the construction of risk assessment models include AHP, VIKOR (Samvedi et al., 2013), grey relational analysis (GRA) (Shojaei & Haeri, 2019), fuzzy comprehensive evaluation (Jun et al., 2018) and entropy weight method. However, AHP is more subjective, with results needing to be constantly evaluated.

TOPSIS is similar to the principle of VIKOR, which are both based on achieving an optimal solution and identifying the worst solution. However, in some cases, optimal and worst solutions are difficult to obtain. Although GRA can be used to select critical factors and reflect the proximity of data when evaluating criteria, it is a qualitative evaluation method. While fuzzy comprehensive evaluation methods can make scientific and reasonable quantitative evaluation possible, the determination of a criteria weight vector is more subjective. By contrast, back propagation artificial neural network (BP-ANN) algorithms can automatically deal with the nonlinear relationship between criteria, and has a strong error tolerance which is helpful for decision-making (Li et al., 2012).

Consequently, this study will adopt the GRA method to select the key risk factors in the processes associated with green supply chains and combine it with the BP-ANN method to evaluate various risks in order to determine the overall level of risk.

GREY RELATION ANALYSIS-BASED RISK FACTOR DETERMINATION

Description of grey relational algorithms

The concept of grey system analysis is aimed to gain an understanding of the uncertainty of a system in which there is "partial information known, partial information unknown" (Julong, 1989). Grey refers to the situation where operating conditions are "poor", "incomplete" and "uncertain". Grey system theory puts forward the concept of grey relational analysis, a method of investigation of a system or subsystems with the objective to identify the numerical relationship between the various factors in the system through a structured investigation. GRA provides a quantitative measure of the development and change of a system. It is based on the similarity of the development trend that exits between factors. This measure can be referred to the "grey relational degree", which is a method for the measurement of the degree of correlation between factors. Grey relational degree and GRA are the foundations of grey system analysis. Associated with GRA is the concept of grey relational clustering. This method of gathering similar data using GRA, which, in turn, allows for the determination of whether or not the sequence curve of experimental data is closely related according to its geometric shape similarity. The closer the curve shape is to reference sequences, the greater the relation between corresponding sequences will be (Julong, 1989).

The specific algorithm steps are as follows：

Determine the reference sequence

To analyze an abstract system or phenomenon, a data sequence (reference sequence) should first be selected which reflects the behavior characteristics of the system. This process is known as the mapping of the behavior of a system and is used to indirectly represent the behavior of the system.

Processing of raw data

Each factor has different units of measurement, with the original data being dissimilar in dimension and order of magnitude, which creates a condition where it is difficult to draw a correct conclusion. Therefore, before calculating the correlation degree, the original data is usually considered as dimensionless.

Let $\mathrm{X_i} = (\mathrm{x_i}(1), \mathrm{x_i}(2), \cdots, \mathrm{x_i}(\mathrm{n}))$ be the behavior sequence of the factor $\mathrm{X_i}$.

（1）Initialization：

$$X_i{}' = \frac{X_i}{x_i(1)} = \left(x_i{}'(1), x_i{}'(2), \cdots, x_i{}'(n)\right), x_i(1) \neq 0, i = 0,1,2,\cdots,m \tag{1}$$

The method of initial value is suitable for the dimensionless state of relatively stable social and economic phenomena, because most of such sequences show a stable growth trend and the growth trend can become more apparent through the processing of the initial value.

(2）Equalization：

$$X_i{}' = \frac{x_i(k)}{\overline{X_1}}, \overline{X_1} = \frac{1}{n}\sum_{k=1}^{n} x_i(k)\,, k = 1,2,\cdots,n \qquad (2)$$

The averaging method is more suitable for data processing where there is no clear trend of increasing or decreasing values.

(3) Interval：

$$X_i{}' = \frac{x_i(k) - \min\limits_k x_i(k)}{\max\limits_k x_i(k) - \min\limits_k x_i(k)}, \quad k = 1,2,\cdots,n \qquad (3)$$

These three methods (dimensionless method, average method, interval method) cannot be used simultaneously. Hence, one of the methods can be selected according to the actual situation when analyzing system factors.

If the system factor $\mathrm{X_i}$ is negatively correlated with the main system behavior $\mathrm{X_0}$, it should be inverted and then calculated.

（4）Invert：

$$X_i{}'' = 1 - x_i(k), \qquad x_i(k) \in [0,1], k = 1,2,\cdots,n \qquad (4)$$

$$X_i{}'' = \frac{1}{x_i(k)}, \qquad x_i(k) \neq 0, k = 1,2,\cdots,n \qquad (5)$$

Calculate correlation coefficient

The reference sequence after data processing is listed as:

$$X_0{}' = \left(x_0{}'(1), x_0{}'(2), \cdots, x_0{}'(n)\right)$$

The comparison sequence is:

$$X_i{}' = \left(x_i{}'(1), x_i{}'(2), \cdots, x_i{}'(n)\right), \quad i = 1,2,\cdots,m$$

From a geometric point of view, the degree of correlation is essentially the similarity between the shape of the reference sequence and the comparison sequence. If the shapes of the two curves are very similar, the correlation between the two is great.

On the contrary, if the shapes of the two curves differ greatly, the correlation between the two is small. Therefore, the difference between curves can be used as a measure of correlation:

$$\Delta_i(k) = |x_0{}'(k) - x_i{}'(k)|, \quad k = 1,2,\cdots,n \tag{6}$$

Maximum and minimum difference between poles is represented as:

$$\begin{aligned} \Delta(\max) &= \max_i \max_k \Delta_i(k), \quad k = 1,2,\cdots,n \\ \Delta(\min) &= \min_i \min_k \Delta_i(k), \quad k = 1,2,\cdots,n \end{aligned} \tag{7}$$

Correlation coefficient is determined by:

$$\gamma_{0i}(k) = \frac{\Delta(min) + \rho\Delta(max)}{\Delta_i(k) + \rho\Delta(max)}, \quad \rho \in (0,1), \ k = 1,2,\cdots,n; \ i = 1,2,\cdots,m \tag{8}$$

If the value of $\Delta\ (Max)$ tends to infinity, the relation coefficient will be less accurate. The differential coefficient ρ is therefore introduced to lessen its influence. The differential coefficient can also improve the significance of the difference between the correlation coefficients.

Calculate and compare degree of correlation

Since the degree of correlation between each comparison sequence and the reference sequence is reflected by n correlation coefficients, the correlation data is scattered (random). It is therefore necessary to centralize the related data. Averaging enables concentrating measurements by calculating the average value of the correlation coefficient between the comparison series and the reference series in each period, and then quantitatively express the degree of correlation between the two series. The calculation formula is:

$$\gamma_{0i} = \frac{1}{n}\sum_{k=1}^{n} \gamma_{0i}(k), \qquad i = 1,2,\cdots,m \tag{9}$$

Risk criteria in a green supply chain

There are many factors influencing the operation of a GSC. Routroy (2009) argues that green raw materials, green design, green operation, green packaging, reverse logistics and green innovation are the main elements of a GSC. Saikis (1998) put forward the notion that a GSC should include the following critical components: internal logistics and procurement, material management, external logistics, packaging and return logistics. Beamon (1999) focused on environmental factors in the supply chain model, proposing a broader supply chain design model that identified novel operational criteria such as resource recovery, waste ratios, and ecological effectiveness. Handfield et al. (1996) provide a comprehensive definition of GSC that includes all of the activities related to the flow and transfer of goods and information. Lijuan (2012) reviewed the existing literature on GSC and summarized the influencing factors as external, internal and intermediate risks.

Based on the above studies, combined with the current understanding of GSCM, the risk factors associated with GSCs can be divided into three primary criteria and 20 secondary criteria (Figure 1).

Due to the large number of influencing factors, this study uses the GRA method to evaluate the risk level of a green supply chain, resulting in an identification of the risk factors with a high degree of influence.

Selection of green supply chain risk criteria based on GRA

As a first step, the expert scoring method is used to determine the relative degree of importance of the selected criteria (Table 1). The rating scale is divided into nine levels**,** "Equally important", "A little important", "Important", "Very important", and "Extremely important" respectively denoted by the scale 1, 3, 5, 7, 9, as well as the criteria between the evaluation, as represented by 2, 4, 6, 8. The evaluation results are shown in Table 2.

The maximum value of each factor is selected as the reference sequence， $X_0 = (9,6,6,3,9,3,5,8,4,4,3,3,6,3,4,6,6,3,6,9)$. The absolute differences were calculated according to Formula (6), with results shown in Table 3.

The maximum difference and the minimum difference are respectively:

$\Delta_{max} = 3$； $\Delta_{min} = 0$

The magnitude of ρ was calculated， $\Delta_k = \frac{175}{20*7} = 1.25$, where 175 is the sum of the absolute differences， $\varphi = \frac{\Delta_k}{\Delta_{max}} = \frac{1.25}{3} = 0.417$， when $\Delta_{max} < 3\Delta_k$， $1.5\varphi \le \rho \le 2\varphi$; when $\Delta_{max} > 3\Delta_k$， $\varphi \le \rho \le 1.5\varphi$

Correlation coefficient is calculated by letting $\rho = 0.7$

$$\zeta_{0i}(t) = \frac{\Delta(min) + \rho\Delta(max)}{\Delta_{0i}(t) + \rho\Delta(max)} = \frac{0 + 0.7 \times 3}{\Delta_{0i}(t) + 0.7 \times 3}$$

Correlation coefficient was calculated by using formulas (7)-(8), with results shown in Table 4. The degree of correlation results, which were calculated by using formula (9), are provided in Table 5.

According to Table 4, C25> C35> C13> C34> C12> C21> C11> C15> C27> C23> C32> C22> C14> C26> C16> C28> C29> C33> C24> C31.

The criteria (factors) with correlation degree >0.63 were selected, which includes: policy, market, natural, consumption, green procurement, green production, green marketing, financial, green recycling, contract, environmental awareness and green design ability.

RISK CLASSIFICATION MODEL BASED ON BP-ANN ANALYSIS OF A GREEN SUPPLY CHAIN

Back Propagation Artificial Neural Network (BP-ANN)

A back propagation (BP) neural network analytical method was first proposed by Rumelhart et al. (1986). It is a multi-layer feedforward network for the backward propagation of errors. BP modeling has the capacity for adaptive learning i.e. it can be "trained". Experimental data is commonly divided into "training samples" and "test samples". Training samples are primarily used to train the model and adjust the parameters of the model. Test samples are used to check the quality of the established model (Sadeghi, 2000). More precisely, input data is fed into the model, and after continuous "training", the best results are obtained. At that point, the relevant parameters of the model are fixed, and the output is considered as the training result.

Furthermore, BP neural networks have a strong nonlinear learning ability which is usually composed of an input layer, a hidden layer and an output layer. The weight between each level is referred to as the connection weight.

The BP algorithm includes two main processes. First, a forward signal propagation i.e. nonlinear conversion action on the output node to produce the output signal. Second, the error back propagation i.e. a process of error propagation from the output layer to the input layer. If the first phase of the actual output and desired output is different, output errors will go step by step through the hidden layer to the input layer, with adjustments being made to the weight and threshold of each layer according to the number of errors. This process is repeated in order to minimize the amount of error, with the experimental process being terminated when a minimal amount of error is achieved. In the BP neural network, data is first propagated back, layer by layer, from the input layer through the hidden layer. When engaged in training in order to determine the network weight, the connection weight of the network is corrected layer by layer from the output layer through the middle layer along the direction of error reduction.

Selection of excitation functions

There are n neurons in the input layer, m neurons in the hidden layer and u neurons in the output layer. The input variable is: $\mathrm{x} = (x_1, x_2, \cdots, x_n)$. The input variable of the hidden layer is: $hi = (hi_1, hi_2, \cdots, hi_m)$. The output variable of the hidden layer is: $\mathrm{ho} = (ho_1, ho_2, \cdots, ho_m)$. The input variable of the output layer is: yi. The output variable of the output layer is: yo. The expected output variable is: yo'. The connection weight of the input layer and the hidden layer is: w_{ih}. The connection weight of hidden layer and output layer is: w_h, $i = 1,2, \cdots, n; h = 1,2, \cdots, m$. The threshold value of each neuron node in the hidden layer is: θ_h. The threshold value of the neuron node in the output layer is: θ. The number of sample data is: $\mathrm{p} = 1,2, \cdots, \mathrm{q}$. The hidden layer excitation function is: $f_1(x)$. The excitation function of the output layer is: $f_2(x)$.

The commonly used excitation functions are: a linear function, s-type transfer function (output range between 0 and 1) and a hyperbolic tangent s-type function (output range between -1 and 1).

$$f(x) = ax + b \tag{10}$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (0 < \mathrm{f(x)} < 1) \tag{11}$$

$$f(x) = \frac{2}{1 + e^{-x}} - 1 \quad (-1 < \mathrm{f(x)} < 1) \tag{12}$$

Selection of the number of hidden layer neurons:

The number of neurons in the hidden layer u can be determined according to an empirical formula along with the number of neurons needed to make the total error reach a minimum value. The common empirical formula is as follows:

$$\mathrm{m} = \sqrt{n + u} + \alpha (1 \leq \alpha \leq 10) \tag{13}$$

$$\mathrm{m} = log_2 n \tag{14}$$

$$\mathrm{m} = 2\mathrm{n} + \mathrm{u} \tag{15}$$

The algorithm steps of a BP neural network:

Step 1: Network initialization. The initial network connection weight, threshold, maximum learning times and error function should be set. Then p, the training sample, which, as previously discussed, was primarily used to train the model and adjust the parameters, is randomly selected， $\mathrm{x(p)} = (x_1(p), x_2(p), \cdots, \mathrm{x_n}(p))$ and expected output is $yo'(p)$.

Step 2: Calculating the input and output of the hidden layer.

$$hi_h(p) = \sum_{i=1}^{n} w_{ih} x_i(p) - \theta_h, h = 1,2,\cdots,m \tag{16}$$

$$ho_h(p) = f_1(hi_h(p)) \tag{17}$$

Step 3: Calculating input and output of the output layer.

$$yi(p) = \sum_{h=1}^{m} w_h ho_h(p) - \theta \tag{18}$$

$$yo(p) = f_2(yi(p)) \tag{19}$$

Step 4: Calculating the error of the output layer and hidden layer.

$$Err_y = yo(1 - yo)(yo' - yo) \tag{20}$$

$$Err_{hi} = yo(1 - yo)Err_y W_h \;\; (h = 1,2,\cdots,m) \tag{21}$$

Step 5: After the adjustment of the threshold of the output layer and hidden layer, the learning rate η was calculated:

$$\theta = \theta + \eta * Err_y \tag{22}$$

$$\theta_h = \theta_h + \eta * Err_{hi}\, , (h = 1,2,3,\cdots,m) \tag{23}$$

Step 6: Calculating the correction value of the connection weight between the hidden layer and the output layer and the correction value of the connection weight between the input and hidden layers.

Step 7: Calculating the total error.

$$\Delta W_h = \eta * Err_y * ho_h(p), . (i = 1,2,\cdots,n; h = 1,2,\cdots,m) \tag{24}$$

$$W_h = W_h + \Delta W_h \tag{25}$$

$$\Delta W_{ih} = \eta * Err_{hi} * x_i(\mathrm{p}), (p = 1,2,3, \dots, m) \tag{26}$$

$$W_{ih} = W_{ih} + \Delta W_{ih} \tag{27}$$

$$\mathrm{E} = \frac{1}{2q}\sum_{p=1}^{q} (yo(p) - yo'(\mathrm{p}))^{2} \tag{28}$$

Step 8: It is determined whether or not the total error is acceptable.

Risk classification of a green supply chain

Determination of criteria parameters:

The GSC risk assessment model presented in this study is built upon a three layer BP neural network model using the following selected criteria: policy factors, market factors, natural factors, consumer factors, green procurement, green production, green marketing, financial factors, green recovery, contract factors, environmental awareness and green design ability with I_1, I_2, I_3, $\cdots$, I_{12}. All of the parameters are shown in Table 5.

Determine learning parameters

（1）Input layer n. 12 evaluation criteria were finally selected for use in this study, with the number of neurons in the input layer being 12 and the input vector denoted as: $\mathrm{x} = (x_1, x_2, \cdots, x_{12})$.

（2）Output layer u. This layer is a sample corresponding to a given output value. The value of the output range refers to the degree of risk situation, ranging from no to high risk (Table 7).

（3）The hidden layer m. The number of neurons in the hidden layer is set as 5. The input vector and output vector of hidden layers are respectively： $\mathrm{hi} = (hi_1, hi_2, \cdots, hi_5)$， $\mathrm{ho} = (ho_1, ho_2, \cdots, ho_5)$.

In a BP-ANN model, the excitation functions of the hidden layer and the output layer are set as a linear function and a s-type transfer function, respectively.

EXPERIMENTAL RESULTS AND ANALYSIS

The GSC risk assessment method proposed in this study is verified by a real case analysis of a Chinese clothing manufacturer (denoted as XY). The apparel company needs to purchase specific materials associated with the production of garments. Significantly, there is increasing stakeholder pressure for the adoption of sustainable practices. As a result, XY Company has developed a GSCM strategy to achieve a competitive strategic advantage.

It is within this context that GSC risk management has been identified as a necessary decision-making activity of XY Company. The method proposed in this study can help XY Company to assess the risk level of its GSC. This case analysis used the factors affecting GSC risk as reviewed in “Risk classification of GSC” (Figure 1).

These standards are expressed as {I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11, I12, I13}. Seven managers responsible from different functional departments of XY Company were invited to express their opinions on the risk rating of the GSC risk factors, which are shown in Table 6. The managers are identified as {E1, E2, E3, E4, E5, E6, E7} which include the company's general manager (E1), strategic purchasing manager (E2), purchasing manager (E3), production department manager (E4), quality control manager (E5), marketing manager (E6), and after-sales manager (E7).

The collected data was randomly divided into training samples and test samples according to a ratio of 8:2. The scoring results were processed and fell within the range of [0,1]. Selected training sample data were used to train the BP-ANN neural network model, resulting in the risk level of the GSC being obtained. Once the trained neural network passed the initial test, it can be used to predict the risk level of an identified GSC.

Step 1: The BP neural network can be trained according to experts' scoring, with regard to risk, of different GSCs. Experts were invited to rate 12 risk factors in 15 groups of GSCs. As shown in Table 8, data numbered 1-12 are used as training samples and data numbered 13-15 are used as test samples.

Step 2: Initial parameter setting of the neural network. According to the empirical formula, the number of hidden layer neurons is set to 5, the number of network iterations is set to 10,000, the expected error target is set to 0.001, with the initial weight value and the minimum training rate being considered default parameters.

Step 3: Network output results are shown in Table 9. According to the results, the risk level corresponding to the output results is very similar to the expected rating level and only one group fails to provide accurate predictions, indicating that the established neural network can basically explain the relationship between inputs and outputs, in terms of risk evaluation.

Step 4: It can be seen from Table 10 that the model has a high degree of accurate fit. It can therefore be deduced that the trained model can be used to effectively predict the risk level of a GSC.

CONCLUSION

In this research study, an integrated GSC risk prediction approach incorporating GRA and BP-ANN is proposed. First, after reviewing the related literature, the risk factors associated with a GSC were summarized, including 3 primary criteria and 20 secondary criteria. Second, based on the analysis of the characteristics of green supply chain risk, the design principles of a GSC risk rating criteria and a criteria evaluation system were proposed. GRA was used to identify the degree of relationship between various factors of supply chain risk, selecting key risk factors and finally arriving at a determination of 12 major risk factors.

Finally, the BP-ANN method was used to determine the risk level of a green supply chain, with simulation experiments being carried out. The experimental results showed that the risk level predicted by the BP-ANN model is robust and suitable for risk assessment in GSCs.

Enhancing the ability to manage supply chain risk is an important guarantee for the sustainable operation of an enterprise. It is significant for companies to prevent or mitigate risk. For managers, the model presented in this paper can be effective to predict risks in the GSC. Results stemming from the model will facilitate the formulation of corresponding countermeasures and strategies to effectively mitigate risk and reduce related costs.

Analyzing the existing research on supply chain risk, this paper not only identified the main risk factors of a GSC, it also proposed a method to interpret the level of risk using BP-ANN. These findings develop a theoretical understanding of GSCs and provide practical implications for managers implementing GSC practices.

The limitations of the study should not be overlooked. The risk criteria discussed in this study are not specific to individual corporations. This drawback has implications for forecasting supply chain risks and managers should therefore assess the importance of the individual risk criteria according to their own conditions.

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