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Developing a Green Supplier Risk Assessment System Applying Natural Language Processing and Life Cycle Assessment: An Empirical Study

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Abstract. Driven by global climate change and Net Zero policies, green supply chain management has become the key to the competition of global enterprises. Carbon emissions and environmental impact have become important factors that must be considered in the supply chain operation process. Among them, supplier selection is the first process in supply chain operation. Although many studies have discussed the related issues of green supplier assessment, the potential risks of some environmental impacts are still not comprehensive enough, plus it is difficult to assess the potential risks of suppliers on the Internet, because the process of text data analysis and evaluation is not only time-consuming and costly, but also unable to obtain the latest supplier risk information on time. This study applies natural language processing(NLP) model and life cycle assessment(LCA) to develop a green supplier risk evaluation system. The potential risk assessment of suppliers can be achieved through the KeyExtractor's keyword extraction method. The main contribution of this study is to develop a novel green supplier evaluation method based on deep learning models to promote the implementation of green procurement and reduce the carbon footprint of suppliers. Practically, the proposed method automates supplier risk assessment, not only can obtain the latest information and trends of supplier risk on time and reduce the time and cost of risk analysis. Hence, the competitiveness of enterprises would be enhanced.

Keywords. Green Supplier Selection, Natural Language Processing, Life Cycle Assessment, Supplier Risk Assessment

Introduction

With the implementation of both Net Zero and the European Union's Carbon Border Adjustment Mechanism (CBAM) policy, carbon emissions have become a cost that must be considered in the commodity manufacturing process, leading to an increase in the importance of selecting green suppliers. Sustainable development has become a core element for enterprises to enhance their competitiveness. Enterprises must find innovative ways to optimize various stages of the supply chain and implement green

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procurement to minimize the carbon footprint, increase their market share, and meet emission reduction requirements [1]. For enterprises, the pressure to maintain a competitive advantage and the urgency to implement sustainable development make selecting green suppliers a necessary condition for operations [2]. Traditionally, supplier selection has focused on quantitative performance metrics such as quality, delivery, speed, and price assessments. However, the importance of more intangible and qualitative criteria, such as supplier involvement, company image, and capability for continuous improvement, is increasing [3]. Supply chains are vulnerable to various sources of uncertainty, and some scholars argue that policies that mitigate risks are needed.

Risk arises from a lack of information, highly uncertain events, and the difficulty of collecting and analyzing risk data. Moreover, assessing supplier risk often requires collecting a large amount of textual information for analysis, and identifying risks is a complicated, time-consuming, and expensive process. Previous research has rarely used deep learning to automatically identify and analyze supplier risks. Therefore, this research aims to identify potential supplier risks by conducting a life cycle assessment and analyzing suppliers' products using the KeyExtractor keyword extraction method of a natural language processing model. The goal is to provide enterprises with quick and accurate access to the latest risk information about their suppliers. This method can also reduce the time and cost of risk analysis, and offer more competitive green supplier risk assessment methods to enterprises.

1. Literature review

1.1. Green Procurement

The main purpose of green supply chain management (GSCM) is to reduce environmental pollution from upstream to downstream, including the purchase of raw materials, manufacturing, distribution, sales, and disposal. It can not only increase market share but also improve enterprise profitability and environmental performance simultaneously. Procurement is a key cross-border function, and upstream suppliers affect the company's environmental impact in many ways. Chen proposed that green procurement is an effective tool for pollution control and prevention, ultimately achieving environmental and economic performance [4]. Enterprises must have a clear green procurement strategy and select sustainable suppliers throughout the supply chain process to meet sustainability requirements [5]. Therefore, choosing the right supplier becomes a crucial issue. As a necessary function of GSCM, green supplier selection plays a vital role in helping enterprises maintain strategic competitiveness [6]. In the selection of suppliers in the environment of green procurement, in addition to the measurement standards of suppliers in the traditional supply chain environment, the environmental performance of suppliers should also be considered. However, environmental performance itself contains multiple standards, and a difficult trade-off must be made among a large number of measurement indicators [7]. Although companies' interest in sustainable supply chain management has greatly increased in recent years, they still lack the ability to incorporate their environmental and social impacts into suppliers' assessments, and most studies tend to focus on cost and quantitative analysis [3]. Therefore, this study uses life cycle assessment (LCA) to provide information for sustainable decision-making in supplier selection and incorporates product carbon footprint and environmental impact analysis into decision-making assessments.

1.2. Supplier Risk Assessment

The business environment is changing at an increasingly rapid rate, and many potential risks associated with this change can be classified as catastrophic [8]. These risks include natural disasters, political tensions, regional instability, and epidemics. What makes these risks particularly challenging is their interconnection with other supply chain risks. Although black swan events are unlikely, they are high-impact risks that are a crucial part of the supply chain risk management approach and cannot be ignored. The occurrence of any one risk has the potential to wreak havoc and affect other risks, making careful risk assessment crucial [9]. The decision-making process is strongly influenced by risk judgments, and any of these types of disruptions can damage an organization's profitability, stock price, and market reputation with significant long-term consequences [10]. Therefore, companies must consider supplier-related risks and threats in their purchasing decisions.Due to the complexity of these networks, supplier risk triggers, their relationships, and consequences are difficult to measure and require dealing with a large number of disparate, distributed data and information sources. Advances in information and communication technologies have increased the scope, variety, volume, and velocity of data, driving businesses to use data-driven decision-making. More and more businesses are starting to use business intelligence and data mining methods to make efficient, intelligent, and timely decisions [11]. However, previous research has not utilized deep learning methods to identify and analyze potential risks of suppliers. Therefore, this research aims to develop a method that can use deep learning to analyze and evaluate the potential risks of suppliers, and provide enterprises with more intelligent and timely tools for automatic risk identification and assessment.

1.3. Application of natural language processing

The development of Natural Language Processing (NLP) has accelerated the speed at which computers can understand and analyze human language. Natural language processing is gradually applied to text analysis to further analyze potential risks. At present, in the field of risk management, the main problem is that unstructured and semi-structured documents cannot be efficiently converted into quantifiable data. Resulting in a lack of effective evaluation of management information by the risk management process, coupled with the fact that text is an expensive process for statistical processing [12]. Careful analysis is required, and it is very time-consuming to find the similarities and differences between different incidents and risks by reading text messages. It is critical to identify these risk factors and take them into account when selecting a supplier. However, it is difficult for the supplier selection team to obtain accurate, complete and up-to-date information [13]. In response to these problems, technology leaders propose to introduce machine learning tools into risk management, and use natural language processing to analyze unstructured files and identify risks. Given that we are in the era of big data, collecting data is no longer a problem, and we can use global insight and knowledge to assess the risks and uncertainties of each supplier. In terms of supply chain management, some researchers have used data from social media to revolutionize their organizations [14]. Su & Chen obtained potential risks and uncertainties of suppliers through text mining, and made better decisions for companies in the global supplier selection process [10] Information on social media is updated rapidly and spreads extremely fast, which provides us with first-hand information [15]. Chiu et al.[16] utilizes deep learning-based natural language processing models for keyword extraction, enabling automatic risk assessment and identification of weaknesses and loopholes in disaster risk analysis. This approach reduces both the time and cost of risk analysisAs natural language models advance, so do the methods for risk analysis and text identification. In 2020, Kim et al. verified that the BERT model had the best keyword extraction performance among various deep models [17]. The evolution and comparison of keyword extraction methods based on natural language processing are shown in the following table (Table 1.):

Table 1. The evolution and comparison of keyword extraction methods.

Method	Pros	Cons
TF-IDF (Li et al., 2007) [18]	Simple and easy to implement, no training required	Limited by the frequency of term occurrence
Word2vec (Wen et al., 2015) [19]	Captures semantic relationships between words	Limited by the size of the training data
Bi-LSTM (Basaldella et al., 2017) [20]	Consider the semantics of the context	Computationally expensive for training
BERT (Tang et al., 2019) [21]	State-of-the-art performance in various NLP tasks	Computationally expensive for training

Although BERT requires manual labeling of key phrases for fine-tuning, this pre-trained model can achieve more accurate keyword extraction with relatively small amounts of labeled data. This research aims to utilize the natural language processing model's keyword extraction method to analyze the risk text information of suppliers. This approach not only enables us to obtain the latest supplier risk information quickly, but also reduces the time required for supplier risk analysis and provides an explanation of the identified risks.

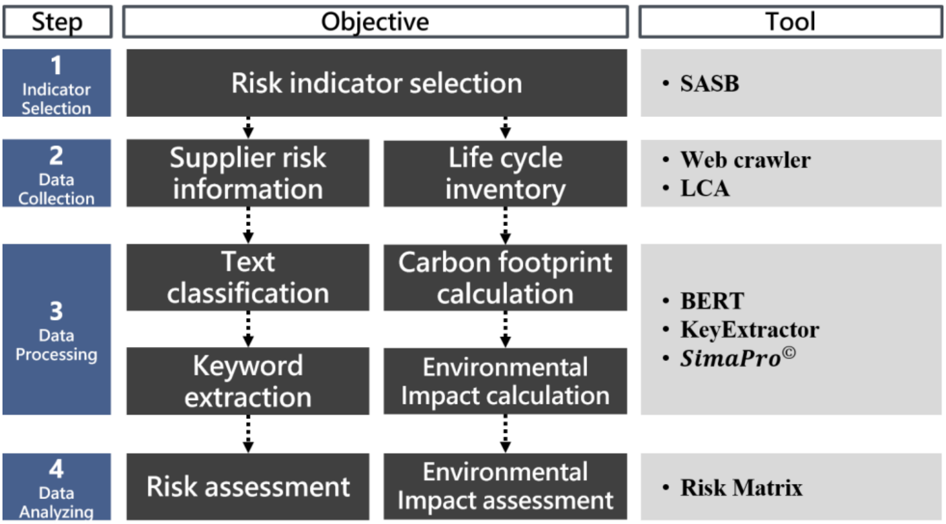

Figure 1. Method flow chart.

2. Methodology

This study proposes the application of a natural language processing model and life cycle assessment to develop a green supplier evaluation system. The system development is divided into four steps as shown in Figure 1. The first step is the selection of risk indicators. The second step is data collection for the two objectives. The first item is the life cycle inventory information of the product, and the second item is the risk information of the product or parts supplier. The third step involves using natural language processing models to classify supplier text information and extract keywords, and using SimaPro to calculate product carbon footprint and environmental impact. The fourth step is to further analyze the processed data and obtain the results of risk ranking and analysis.

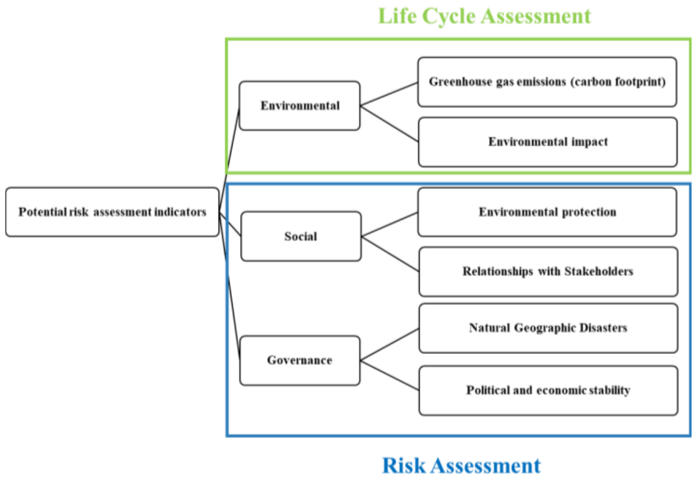

Figure 2. Risk assessment indicator tree diagram.

2.1. Data collection

Based on the ESG assessment dimensions benchmark, this research is organized according to the green supplier selection criteria proposed by Chiou et al. and Gao et al. in the electronics industry [2][22]. The standard is used as an indicator for evaluating the potential risks of green suppliers in this study, as shown in Figure 2. The evaluation indicators are classified into three major aspects: environmental protection, social responsibility, and corporate governance, and supplier information is collected according to these indicators. Among them, the risk information collection of suppliers uses a web crawler to automatically browse the web and collect the required supplier information. Treat the collected information as text, t_{title} is the title of the text, $t_{content}$ is the content of the text, and t t_{date} is the time when the text was released, which is defined as formula (1):

$$t = (t_{title}, t_{content}, t_{date}) \quad (1)$$

2.2. Data processing

2.2.1. Text classification

In this study, the supplier text dataset t is pre-processed, including the removal of punctuation marks, stop words, and sentence segmentation. To process the text data, this study uses BERT (Bidirectional Encoder Representations from Transformers) for transfer learning. BERT is a pre-trained context learning, two-way, unsupervised transformer model that carefully identifies "each word" of the search string and understands the meaning of the entire search string based on the relationship between preceding and following words. Unlike in the past, which only selects one word to compare with the previous or next word, the BERT algorithm takes the entire sentence into reference for judging the semantics, allowing for more accurate judgment of the user's intention and purpose in searching for the word string. BERT can convert short sentences and articles into meaningful vectors, with the advantage of solving a wide variety of natural language processing problems using the same pre-trained model. The model architecture diagram is shown in Figure 3, which can be divided into two steps: pre-training and fine-tuning. In the pre-training stage, Google uses a large amount of text data to train the model based on unsupervised learning. In the fine-tuning stage, labeled data is used to train and fine-tune the model for different tasks [23].

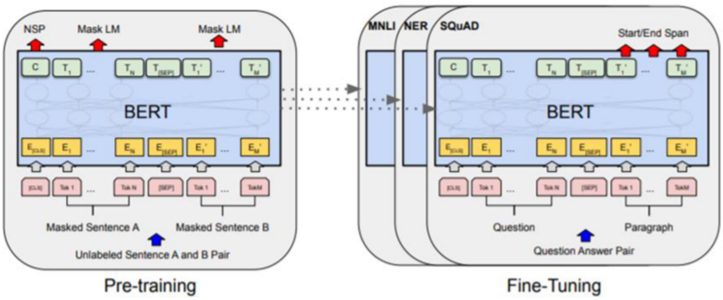

Figure 3. Architecture diagram of BERT [24].

The fine-tuning in this research is to connect a new classification layer to do downstream tasks, to train the entire network using a small amount of text, while fine-tuning the hyperparameters. This study collects news texts from multiple companies, and then labels these texts. The classification labels are divided into 5 items, 4 of which are the 4 indicators of risk assessment in Figure 2, and other text categories are classified as "others."

2.2.2. KeyExtractor: Keyword extraction technology using BERT

This study utilizes the traditional Chinese keyword extraction technology KeyExtractor to extract keywords from text. KeyExtractor uses BERT embeddings and cosine similarity to identify words or phrases in the text that are most similar to the text itself, while considering context and semantics. The pre-training model embedded in KeyExtractor selected bert-base-chinese, proposed by Taiwan Academia Sinica Information, due to its outstanding performance in word segmentation. The model achieved an F1 score of 97.60% in the word segmentation task and exhibited the lowest degree of confusion, as shown in Table 2. This task is an important indicator for keyword and keyphrase extraction.

Table 2. Comparison of the performance of each model on the word segmentation task.

Model	Parameters	Perplexity	Word segmentation
ckiplab/albert-tiny-chinese	4M	4.80	96.66%
ckiplab/albert-base-chinese	11M	2.65	97.33%
ckiplab/bert-tiny-chinese	12M	8.07	96.98%
ckiplab/bert-base-chinese	102M	1.88	97.60%

In this study, the pre-processed supplier risk information was first subjected to keyword extraction using KeyExtractor, and then cosine similarity calculation was performed between the extracted keywords and the text dataset. The similarity between two vectors is measured by computing the cosine value of the angle between them, which helps in selecting the most relevant keywords to the text. The cosine similarity θ between two attribute vectors, A and B, is given by the dot product of the two vectors and the product of their vector lengths, and the similarity ranges from -1 to 1, as shown in Equation (2):

$$Cosine\ Similarity\ = \cos\theta = \frac{A \cdot B}{\|A\|\|B\|} \quad (2)$$

2.2.3. Product Carbon Footprint Verification

This study takes gate-to-gate as the research category. In the case of meeting the same functional unit, calculate the carbon emissions of the product at each stage. Carry out carbon footprint analysis based on the life cycle of the product, and analyze its impact on the environment. The carbon footprint calculation formula (3) is as follows:

$$\text{Carbon Footprint}(CO_2\text{e}) = \sum(Activity\ data, \times\ Emission\ factors \times GWP\ value) \quad (3)$$

2.3. Data analyzing

2.3.1. Supplier Risk Assessment and Analysis

This research refers to the ISO9001:2015 risk management approach to classify the severity of supplier risks and their impacts. This study divides supplier risk into three risk levels and three risk severity levels. The keywords extracted from the supplier information data set are converted into a risk assessment matrix according to the risk level, the risk level of risk severity analysis indicators, and the severity of risks suffered by the enterprise, as shown in Table 3. The risk level is rated from 1 to 9. Formula (4) is as follows:

$$\text{Risk level} = Severity\ of\ risk \times Probability\ of\ risk \quad (4)$$

Table 3. Risk Matrix.

Risk level		Probability of risk		
		P1(1)	**P2(2)**	**P3(3)**
Severity of risk	**S3(3)**	Moderate (3)	High (6)	High (9)
	S2(2)	Low(2)	Moderate (4)	High (6)
	S1(1)	Low (1)	Low (2)	Moderate (3)

3. Case Study

This case study takes company D as an example, which is an electronic product manufacturer with a total capital of NT$4 billion. This study takes the key parts suppliers A, B, and C of a certain product of the company as a case study. The data sources include the text information of the three suppliers' web crawlers and the life cycle assessment checklist of the three suppliers. The scope of the inventory is from the input of production to the output and the mode of transportation of the product manufacturing stage.

3.1.1. Text Classification Model Training

This research uses crawlers to collect text data from technology companies in Taiwan from 9 news websites and manually labels them into five categories according to the content of the text data, which are four indicators of risk assessment and others. The number of information on each label is 191 for environmental protection, 890 for relations with stakeholders, 123 for natural and geographical disasters, 1308 for political and economic stability, 120 entries for others, totaling 2632 entries.Then, the classification layer of the last layer of the BERT model was fine-tuned to the five classifications of this study, and the above-mentioned label data was used for model training. The accuracy rate is 72.8%, and the F1-score is 71.3%.

3.1.2. Keyword extraction

Referring to the risk matrix shown in Table 4,the analysis indicates that supplier A's relationship with stakeholders and political and economic stability are all considered moderate risks, which are within tolerable levels. It is recommended to review the keyword extraction results to understand why these risks have been identified and to assess whether preventive measures or scenario predictions should be considered.

Table 4. Supplier Risk Matrix.

Risk indicator\Supplier	Supplier A	Supplier B	Supplier C
Environmental protection	1	1	1
Relationships with Stakeholders	3	2	1
Natural Geographic Disasters	1	2	1
Political and economic stability	4	3	1

3.1.3. Life cycle assessment

Calculated by formula (3), the carbon footprint of the three suppliers in the system boundary is gate-to-gate, as shown in Table 5. The activity data in the calculation formula is the half-year energy and resource input data of the factory area provided by the supplier, and the emission coefficient is the characteristic value of IPCC 2021 GWP 100. The distribution principle of the calculation is that the main raw material input, auxiliary material input and energy resource consumption are all distributed according to the output ratio of each product.

Table 5. LCA Carbon Inventory Result.

Evaluation objects	Data calculation
Supplier A	83.92 kg-CO2e/pcs
Supplier B	1142.60 kg-CO2e/pcs
Supplier C	943.57 kg-CO2e/pcs

In order to evaluate the environmental impact of the manufacturing and transportation of the three suppliers, this study uses the Eco-indicator 95 V2.06 / Europe e assessment method. The impact categories include Greenhouse, Ozone layer, Acidification, Eutrophication, Heavy metals, carcinomaogen, Pesticides, smog, Energy resources, Solid waste and other 11 categories.

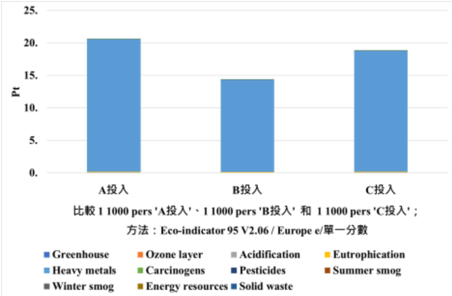

Figure 4. Environmental impact assessment results of the manufacturing stage of the three suppliers.

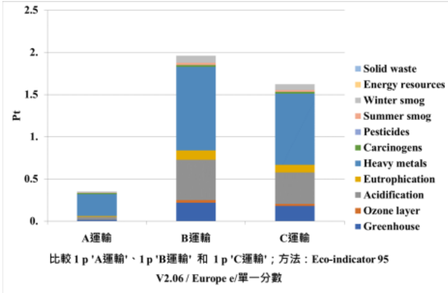

Figure 5. Environmental impact assessment results of the three suppliers during the transportation phase.

Figures 4 and 5 present the environmental impact of three suppliers at different stages within the scope of door-to-door delivery. In terms of the input stage, solder paste, solder bars, and solder wires have higher input proportions, resulting in heavy metals having the highest share in environmental impact. In the transportation stage, suppliers B and C utilize air and sea transport, leading to significantly higher environmental impact compared to supplier A, which relies solely on land transport. The cumulative environmental impact of the two stages serves as the final evaluation indicator. The results indicate that the overall impact, ranked from high to low based on the cumulative assessment, is as follows: Supplier A (0.37Pt), Supplier C (1.98Pt), Supplier B (1.64Pt). It can be observed that if suppliers choose air or sea transport for long-distance shipment, it will result in higher environmental impact and increased carbon costs in product manufacturing

4. Conclusion

This study aims to bridge the research gap by proposing the application of natural language processing and life cycle assessment to develop a green supplier risk assessment system. The main contributions are summarized in the following two points. First, the method proposed in this study provides a specific green supplier risk assessment method for enterprises, promotes the implementation of green procurement, and facilitates sustainable development and risk management of key suppliers.Second, this study uses self-collected and labeled datasets to fine-tune the natural language processing model, conduct text classification and keyword extraction of risk indicators, and analyze supplier risks to obtain the latest information on supplier risks more quickly and accurately, reducing the time and cost associated with risk analysis.

Future research can incorporate more rigorous risk assessment indicators into the assessment system to facilitate the consideration of a wider range of risk factors. Additionally, the weight of corporate procurement assessment priorities should be taken into account to enhance the value of the green supplier assessment system and enable it to become a supportive decision-making system for corporate procurement.

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