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EVALUATING SUPPLY CHAIN RESOURCE LIMITS FROM NEWS ARTICLES AND EARNINGS CALL TRANSCRIPTS: AN APPLICATION OF INTEGRATED FACTOR ANALYSIS AND ANALYTICAL NETWORK PROCESS

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ABSTRACT

Due to the impact of globalization, companies have extended their borders across nations to launch products more competitively. However, globalization affects various uncertainties and risks that may limit the performance of supply chains. Research indicates that models that incorporate uncertainties and risks will help to improve the resilience of global supply chains. In the era of technology, we experience the abundance of textual data from various web-media resources related to companies, which can be deployed to understand the impact of risks on the chain. Accordingly, this study aims to utilize textual data collected from news articles and earnings call transcripts to assess the vulnerability of the suppliers and the chain. Among many, we considered supply chain resource limits as a subcomponent of vulnerability and collected textual data associated with its sub-factors. Then, we proposed an integrated factor analysis and Analytical Network Process (ANP) method to model the company's supply chain resource limits index. Specifically, factor analysis was used to determine the latent constructs of the variables that are grouped under resource limits and their correlations. This latent construct and correlations were then applied as the interdependencies among variables in the ANP to discover the final importance weights of the variables in terms of supply chain resource limits. The results of the study showed that the shortages of capacity, components, and energy supply are the most critical sub-factors. The company's supply chain resource limits index (SCRLI) can be further calculated to assist decision-makers of an enterprise in supply chain configuration design, and improve the supply chain resilience.

Keywords: Supply chain management; Text analytics; Factor analysis; Analytical Network Process (ANP)

1. INTRODUCTION

With the development of information technologies and the increase in globalization, companies incorporate suppliers from multiple nations into their networks to decrease costs. Therefore, several companies today have global supply chains that extend beyond national borders. To optimize the cost and benefit, Meixell and Gargeya [1] suggested that both manufacturers and suppliers in the multiple tiers of the supply chain should be integrated into the global supply chain design problems. However, in addition to the cost benefits, global supply chains have additional risks compared to the supply chains that operate in a single nation. Such risks include political issues, technological replacement, demand fluctuations, natural disasters, and global financial crisis [2, 3]; and models considering these risks may directly benefit the performance of the global supply chain [4].

Supply chain risks are often connected with supply chain resilience, which is a critical concept in supply chain management. There have been numerous studies conducted on supply chain resilience and its relationship with conventional risk management. Some studies have asserted that resilience can be observed as a concept of Zone of Balanced Resilience, where resilience can be decomposed into aspects of capabilities and vulnerabilities [5, 6]. Capabilities are the characteristics that allow a company to deal with disruptions, and vulnerabilities, or adverse consequences and related event probabilities.

Although research about supply chain resilience has been flourishing throughout the decade, researchers mainly discussed conceptual frameworks or applied qualitative methods such as interviews and focus groups on addressing supply chain resilience problems. Moreover, studies lack discussions on the interdependencies among the factors of resilience. Among the reasons

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for limited quantitative analyses of the supply chain resilience problem are (1) numerous uncertainties that would affect a supply chain, and (2) the abundance of resilience factors, including those that cannot be measured quantitatively. Another critical reason is that most company information related to their manufacturing, marketing, and operations is considered confidential. In other words, even though quantitative data exists, it may still not be accessible by other companies.

The above-explained context has led to a rising trend towards using text data from social media and news articles to assist in evaluating supply chain resilience. Recently, researchers have used different text mining techniques to analyze text sources for supply chain resilience management [7, 8]. Unlike the confidential company information, the text data in news articles and social media are often open access. This presents a means to evaluate supplier capabilities and vulnerabilities utilizing this open access text data, and in turn, greatly enhancing insights for strategic use in a competitive setting.

Based on the above summarized background, the research questions of this study are as follows: (i) What are the interrelationships among resilience factors?, and (ii) How can the open-access text data be incorporated in managing supply chain resilience? Accordingly, we aim at utilizing open access text data (news articles and earnings call transcripts related to the technology sectors) to evaluate supply chain resilience. The focus is placed on developing a scoring method for one of the critical factors, "resource limits," related to supply chain vulnerability proposed by Pettit et al. [5, 6]. Different from their study, regular expressions are applied to detect the number of documents related to the sub-factors under "resource limits." An integrated factor analysis (FA) and analytical network process (ANP) method is conducted to reveal the latent constructs and associated weights of the sub-factors of "resource limits." Finally, a company's supply chain resource limits index (SCRLI) is calculated based on its list of major suppliers, normalized document detection counts, and the importance weights of the sub-factors.

2. LITERATURE REVIEW

2.1 Global supply chain

Typically, the global supply chain problem deals with deciding the quantities and movement of the products from the points of origin to the consumers located in different nations [1]. Deciding the facilities and their capacities, procurement quantities of the goods and supplier selection are the significant problems of global supply chains that regularly involve various uncertainties and risks. In the literature, there are a considerable number of studies that focus on the global supply chain problems from the risk and uncertainty perspectives. Among the many, Ding, Dong, and Kouvelis [9] built a two-stage stochastic model for the capacity allocation problem under exchange rate and demand risk. Goh, Lim, and Meng [10] proposed a multi-stage stochastic programming model for the global supply chain problem considering the uncertainties in demand, exchange rates, tax rates, and import tariffs to maximize the profit of the company. Singh et al. [11] proposed a scenario-based optimization model for the global supply chain problem under several risks such as exchange rates, quality problems, late shipment, etc. Bandaly, Satir, and Shanker [12] developed a stochastic integrated risk management model to manage the operational and financial risks in the supply chain for a beer production company. Their model provided optimal operational risk management (i.e., when to order aluminum sheets, inventory level) and a financial risk management (i.e., the fluctuation in the aluminum price) strategy for the company under fluctuation in the price of aluminum cans and uncertainty in beer demand. Kim and Park [13] analyzed the supply chain contracts where the exchange rate risk can be transferred to the third party, i.e., bank, or shared between the supplier and the buyer. They investigated the effect of those contracts to improve the utility of the supply chain by comparing the case where no contract is made for a decentralized supply chain. Gylling et al. [14] stated that the cost-benefit of offshoring decreases due to uncertainties in the market, such as increased exchange rates, volatility in customer demands, and demand-supply mismatch. The authors discussed the backshore decision of a bicycle company in regards to the diminishing benefit of offshoring. Hasani and Khosrojerdi [15] proposed a mixed-integer nonlinear model to optimize the net profit of the company under procurement and demand uncertainties.

Other studies investigated the global supply chain risk assessment with a focus on how to measure and assess the risk for their supply chains and, at the same time, how to design their chains accordingly to mitigate the impact of risks. Venkatesh, Rathi, and Patwa [16] developed a risk prioritization model by utilizing interpretive structural modeling (ISM). Safety and security of resources, labor issues, and globalization were considered as triggers of the supply chain uncertainties. Aqlan and Lam [17] proposed an integrated framework that uses fuzzy logic, supplier surveys, and Bow-Tie analysis to assess potential supply chain risks. Ghadge et al. [18] integrated a fuzzy logic approach into failure mode and effect analysis (FMEA) to understand the failure modes and their associated risks for products and processes within a global supply chain content. The objective was to proactively mitigate the impact of the main risk causes before they occur. Giannakis and Papadopoulos [19] proposed an FMEA technique to analyze the impact of operational risks to its supply chain. Aqlan [20] proposed a software tool that utilizes survey, probability theory, and fuzzy logic to assess product-based risks in the supply chain. The model allows supply chain risk experts to input the risk estimates and their likelihood through a survey. Then, considering these estimates, the risk scores are calculated for the products. A case study was conducted for a manufacturing company to verify the model. Rostamzadeh et al. [3] proposed a sustainable supply chain risk management evaluation framework utilizing fuzzy logic and TOPSIS. The main risk factors considered in the study were environmental risks, organizational risks, sustainable supply risks, sustainable production/manufacturer risks, sustainable distribution risks, sustainable recycling risks, and information technology-related risks. According to the created platform, the risk of suppliers in the petrochemical industry was assessed. Choi et al. [21] analyzed the supply chain literature in order to determine how the mean-variance approach could be applied to examine the risk factors in air logistics and blockchain technology. The authors reviewed studies that considered air logistics operations, demand management, supply management, and supply-demand coordination, and then discussed how the blockchain application might help to decrease the risks originated from demand and supply. The review conducted by Baryannis et al. [22] summarized state-of-the-art studies in the supply chain that consider risk management and discussed the many research techniques, including statistics, optimization, and simulation. Vanalle et al. [23] surveyed auto parts producers to determine the risks for the first- and second-tiers of the automobile sector supply chain. Results showed that the risks perceived from the second tier are higher than those of the first-tier suppliers in the chain. Dias, Hernandez, and Oliveira [24] determined the risk factors for the automobile sector through a survey and then applied the Analytic Hierarchy Process (AHP) to rank the risks. The developed instrument provides a platform to assess the risk score for automobile companies.

2.2 AHP and ANP

AHP is aanalysis framework for solving decision-making problems with multiple independent criteria. Since introduced by Saaty [25], AHP was extensively used by researchers due to its ability to cope with qualitative criteria and multiple decision-makers and to integrate with other decision-making methodologies. Emrouznejad and Marra [26] discussed the development and use of AHP over time as a standalone method and in integrations with other techniques including fuzzy logic, the technique for order preference by similarity to ideal solution (TOPSIS) and Data Envelopment Analysis (DEA). The authors used overlay mapping and social network analysis (SNA) in mapping citations of 8441 AHP related published articles to identify studies with the most influence over AHP history. AHP has been used widely across fields of research. Joel, Ernest, and Ajapnwa [27] presented an AHP model to identify the most appropriate strategy to manage municipal solid wastes in Yaoundé, Cameroon. Wang et al. [28] combined Monte Carlo simulation and AHP to enhance confidence in the determination of the optimum method to mine coal in thin seams. Saxena and Jat [29] integrated AHP into SLEUTH (slope, land cover, excluded regions, urban land cover, transportation, and hill shade) to enhance the sustainability in urban growth modeling. Suhanto et al. [30] used AHP to identify technology, organization, and environmental factors critical to the success of data integration in a hybrid cloud. Liu et al. [31] presented a human reliability analysis AHP model to investigate the critical factors that influence the cognitive performance of operators during the monitoring, decision-making, and execution of actions in the control rooms of nuclear power plants based on simulated data.

ANP is a network form of AHP that is used for multi-criteria decision making, where the criteria do not have to be independent [32]. In recent literature, Kheybari, Rezaie, and Farazmand [33] categorized 456 ANP related papers into nine categories based on the field of application. The authors also investigated the integration of ANP with other decision-making techniques, where fuzzy logic, FANP, was the most integrated technique. Wicher, Zapletal, and Lenort [34] used FANP to assess the performance of industrial organizations with a focus on sustainability. Shafiee et al. [35] proposed a model that integrates ANP and cost-risk criticality analysis to find a maintenance strategy that is both cost-effective and of low-risk. The authors applied the model to select a strategy among failure-based, time-based, risk-based, and condition-based alternatives to maintain mechanical, electrical, and auxiliary systems in a wind turbine. Simwanda, Murayama, and Ranagalage [36] presented an ANP model to investigate influential factors that drives change in urban land usage in Lusaka, Zambia. The author shows that socio-economic and population factors were the most influential drivers. Lancharoen, Suksawang, and Naenna [37] used ANP to assess the readiness for integrating information in hospitals in Thailand to form a healthcare network to enhance performance and improve healthcare delivery.

3. METHODOLOGY

This study integrates FA and ANP to analyze text data from news articles and earnings call transcripts for evaluating “resource limits,” one of the critical factors under supply chain vulnerabilities presented by Pettit et al. [5, 6]. Figure 1 provides the flow of the proposed methodology.

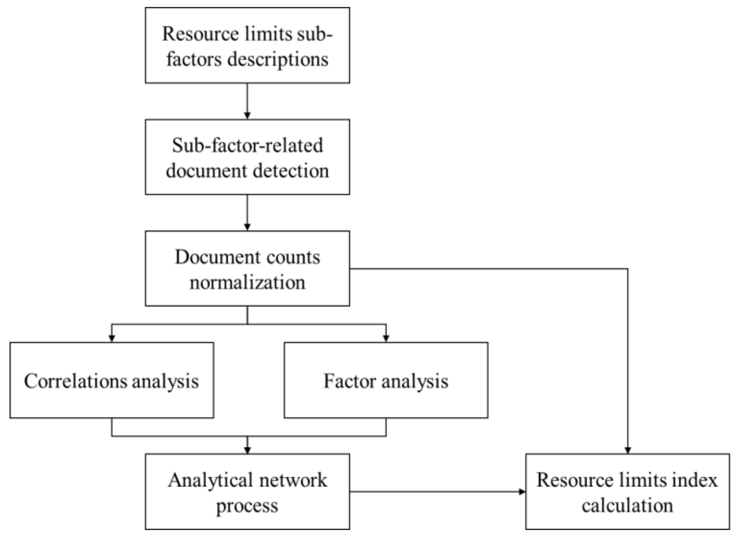

FIGURE 1: RESOURCE LIMITS INDEX DEVELOPMENT.

First, resource limits evaluation is the main focus of this study. According to Pettit et al. [5, 6], resource limits are “constraints on output based on the availability of the factors of production,” under which the authors identified 17 sub-factors (variables). Table 1 presents the variables’ titles, symbolic abbreviations, descriptions, and directions of contribution to supply chain resilience.

Second, regular expressions are utilized to design automatic classifiers for collecting the documents related to each variable. The classifiers detect documents having sentences that mention the related topics based on word proximity, and they also record the published date and company information. In this study, financial news articles and earnings call transcripts were the primary text sources. Since different industries might have different supply chain characteristics and design focuses, we limited our dataset to a sub-sample of Russell 1000 firms belonging to the technology sectors. The final dataset was in the form of an aggregated document detection counts across companies in the technology sector for each study variable each month, starting from January 2003 to November 2017. The reason for reorganizing the document counts into monthly data format is to observe the impact of resource limits on economic changes throughout the timeline. On the other hand, the reason for aggregating the counts in one technology sector is to discover the specific variable interdependencies and importance weights for this specific sector, i.e., technology. However, it is essential to mention that the data collection process, in general, can be used for different sectors as well.

Third, after collecting and reorganizing the dataset, normalization was conducted for each variable. To calculate the level of vulnerability, the counts of all variables in Table 1 are multiplied by a negative sign. That is, a variable with a negative contribution to resilience will have a positive contribution to vulnerability. If the value of a variable with a positive contribution to vulnerability in a month increased, it means that the company was more vulnerable in terms of that variable during that month. The final value of the data is arbitrary, and this needs to be normalized over a range from 1 (least vulnerable/most resilient) to 10 (least resilient/most vulnerable).

Fourth, correlation and factor analysis are implemented to the normalized dataset to reveal the latent construct (main factors) of the variables using the R statistical tool.

The outcome latent construct is used as the network structure of ANP in the last phase. Some extant studies used factor loadings from the factor analysis and correlation coefficients of variables as direct inputs of ANP [38, 39]. This is a way to prevent from getting biased results based on subjective judgment. The local priorities generated from pairwise comparisons are further converted into an unweighted super-matrix. The final variable importance weights are then calculated from the weighted super-matrix and convergent limit super-matrix. The ANP calculations are carried out by Super Decision software [40].

The final step is to apply the importance weights obtained from ANP to calculate the company resource limits index (CRLI) by summing up the weighted normalized document counts for each resource limits variables of a company (Eq. 1). Then, a company's supply chain resource limits vulnerability index (SCRLI) is evaluated by averaging the company resource limit indices for its critical suppliers (Eq. 2). The equations are as below:

$$CRLI = \sum_{i=1}^{n} (W_i \times R_i) \tag{1}$$

where CRLI is the company resource limits index, W_i is the importance weights of i^{th} variable derived from ANP limit super-matrix, and R_i is the normalized document counts derived from the resource limits automatic document classifier.

$$SCRLI = \frac{\sum_{j=1}^{N} CRLI_j}{N} \tag{2}$$

where SCRLI is the supply chain resource limits index, indicating the condition of a company's overall resource limits vulnerability, j represents the jth critical suppliers of the target company, and N is the total number of the critical suppliers.

TABLE 1: VARIABLES RELATED TO RESOURCE LIMITS IN SUPPLY CHAIN RESILIENCE.

Variable title	Variable symbol	Description	Contribution to resilience
Transportation disruption	TD	Number of documents on transportation disruptions impacting the company.	Negative
Capacity increase	CAI	Number of documents related to capacity increase impacting the company.	Positive
Capacity decrease	CAD	Number of documents on capacity decrease impacting the company.	Negative
Capacity shortage	CAS	Number of documents talking about capacity shortage impacting the company.	Negative
Patent disputes	PD	Number of documents talking about patent disputes impacting the company.	Negative
Research restrictions	RR	Number of documents talking about research restrictions impacting the company.	Negative
Product obsolescence	PRO	Number of documents talking about product obsolescence impacting the company.	Negative
Supply increase	SI	Number of documents talking about supply increase impacting the company.	Positive
Supply decrease	SD	Number of documents talking about supply decrease impacting the company.	Negative
Component shortage	CPS	Number of documents talking about component shortage impacting the company.	Negative
Stock warehouse concerns	SWC	Number of documents talking about inventory/warehouse concerns impacting the company.	Negative

Assembly bottleneck	AB	Number of documents messaging on assembly bottlenecks impacting the company.	Negative
Power outage	PO	Number of documents talking about power outage impacting the company.	Negative
Equipment failure	EF	Number of documents on equipment failure impacting the company.	Negative
Negligent maintenance	NM	Number of documents talking about negligent maintenance impacting the company.	Negative
Plant opening	PLO	Number of documents talking about plant opening impacting the company.	Positive
Plant closure	PLC	Number of documents talking about plant closure impacting the company.	Negative

4. RESULTS AND DISCUSSION

4.1 Factor analysis

Following the dataset normalization phase, the final normalized dataset is used in FA to reveal latent factors that capture the main variance structure of resource limits using R statistical tool.

To determine the number of factors extracted from the variables, the eigenvalues of the factors are calculated, and only factors with eigenvalues greater than or equal to one are used for further analysis. Moreover, Oblimin rotation is used to obtain non-orthogonal factors, meaning that latent factors are assumed interdependent. Several model fits are also calculated to select a better model with different numbers of factors. Table 2 shows the different model fit statistics. The best scenario of absolute model fits is when the p-value of Chi-square test is greater than 0.05 (i.e., the null hypothesis, which is the model and original data are consistent, is not rejected), Tucker-Lewis Index is greater than 0.90, and the root mean square error is smaller than 0.05. No models in this study met all these criteria. With further analysis and review, and based on Bayesian information criterion, which is a relative goodness of fit statistic that is used to compare models when lower values of Bayesian information criterion are preferred, the model with four latent factors is selected. Table 3 shows the results of the four-factor FA model.

TABLE 2: FA MODEL FITS.

Number of factors	P-value of Chi-square test	Tucker-Lewis Index (TLI)	Root mean square error approximation (RMSEA)	Bayesian information criterion (BIC)
2	1.5e-82	0.813	0.197	206.81
3	3e-36	0.889	0.152	-5.4
4	1.1e-16	0.93	0.12	-81.77

TABLE 3: FACTOR LOADINGS OF THE FA MODEL.

Variables	Factor 1	Factor 2	Factor 3	Factor 4
PLO	-1.00	0.05	-0.04	0.05
PRO	0.98	0.02	-0.04	-0.04
TD	0.83	-0.02	0.14	-0.02
CAI	-0.83	-0.08	-0.03	-0.14
SI	-0.81	-0.10	0.05	-0.18
EF	0.75	0.14	0.02	0.02
PD	0.71	0.11	-0.01	0.12
RR	0.54	-0.01	-0.13	-0.27
CAD	-0.08	1.00	-0.05	0.02
SD	0.14	0.80	0.10	0.00
PLC	0.19	0.73	0.07	-0.10
AB	0.31	0.44	0.14	0.23
PO	0.00	0.02	0.83	-0.04
CAS	0.29	0.08	-0.02	0.60
CPS	0.07	0.07	0.46	0.48

In this FA model, 80% of the total variance is explained by the four latent factors (43% by factor 1, 22% by factor 2, and 8% by factors 3 and 4). Since Oblimin rotation is used, the correlations among factors are also calculated. Figure 2 presents the visualization of the FA model with factor correlations. The linkage between a factor and a variable indicates that this variable is highly correlated to the parent factor, and the factor loading is represented by the correlation coefficient. Note that due to the insufficient document counts for variable SWC and NM, and hence their incompatibility with the FA model, these two variables were removed from the dataset and the further ANP analysis.

4.2 Analytical network process

The FA model is converted to an ANP structure using Super Decision software (Figure 3). Instead of asking survey questions to obtain pairwise comparisons from the subjective expert judgment in conventional ANP, correlations among the 15 variables, factor loadings of each variable to the corresponding factors, proportional variance explained by each factor, and correlations among factors are used as the inputs of the unweighted super-matrix (Table 4). The weighted super-matrix (Table 5) is then calculated, taking into consideration the local priorities of the four factors, derived from the proportional variance explained by each factor. Finally, the limit super-matrix is generated with the final importance weights for each variable by multiplying the weighted super-matrix by itself to the n^{th} power to attain convergence. Table 6 demonstrates the final weighting values for each resource limit variable.

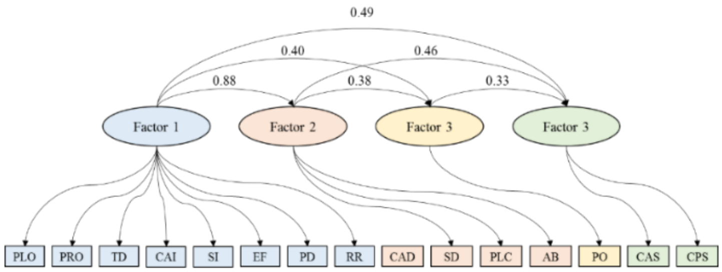

FIGURE 2: FA MODEL.

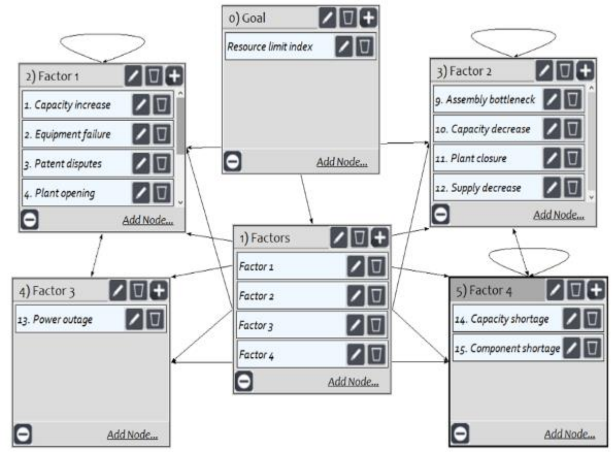

FIGURE 3: ANP STRUCTURE BY SUPER DECISION [40].

TABLE 4: UNWEIGHTED SUPER-MATRIX.

		0) Goal	1) Factors				2) Factor 1								3) Factor 2				4) Factor	5) Factor 4	
		Resource	Factor 1	Factor 2	Factor 3	Factor 4	1. Capaci	2. Equipm	3. Patent (	4. Plant o	5. Produc	6. Resear	7. Supply	8. Transp	9. Asseml	10. Capac	11. Plant (	12. Suppl	13. Power	14. Capac	15. Comp
0) Goal	Resource limit index	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1) Factors	Factor 1	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Factor 2	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Factor 3	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Factor 4	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2) Factor 1	1. Capacity increase	0.00	0.13	0.00	0.00	0.00	0.00	0.17	0.16	0.17	0.17	0.14	0.17	0.16	0.15	0.15	0.14	0.14	0.16	0.16	0.16
	2. Equipment failure	0.00	0.12	0.00	0.00	0.00	0.15	0.00	0.15	0.15	0.15	0.13	0.15	0.15	0.13	0.13	0.13	0.13	0.15	0.14	0.13
	3. Patent disputes	0.00	0.11	0.00	0.00	0.00	0.15	0.15	0.00	0.15	0.15	0.12	0.15	0.15	0.13	0.13	0.13	0.13	0.12	0.14	0.14
	4. Plant opening	0.00	0.16	0.00	0.00	0.00	0.17	0.17	0.17	0.00	0.17	0.17	0.17	0.17	0.14	0.14	0.14	0.14	0.15	0.14	0.15
	5. Product obsolescence	0.00	0.15	0.00	0.00	0.00	0.16	0.16	0.16	0.16	0.00	0.18	0.16	0.16	0.13	0.14	0.14	0.14	0.13	0.14	0.13
	6. Research restrictions	0.00	0.08	0.00	0.00	0.00	0.05	0.05	0.05	0.06	0.07	0.00	0.05	0.05	0.04	0.05	0.05	0.04	0.00	0.00	0.00
	7. Supply Increase	0.00	0.12	0.00	0.00	0.00	0.17	0.17	0.16	0.16	0.16	0.14	0.00	0.16	0.15	0.14	0.14	0.15	0.13	0.16	0.15
	8. Transportation disruption	0.00	0.13	0.00	0.00	0.00	0.14	0.15	0.15	0.15	0.14	0.12	0.14	0.00	0.13	0.12	0.13	0.13	0.16	0.12	0.14
3) Factor 2	9. Assembly bottleneck	0.00	0.00	0.15	0.00	0.00	0.26	0.25	0.25	0.25	0.23	0.20	0.26	0.26	0.00	0.31	0.31	0.32	0.29	0.28	0.30
	10. Capacity decrease	0.00	0.00	0.35	0.00	0.00	0.25	0.27	0.27	0.25	0.28	0.26	0.25	0.24	0.34	0.00	0.35	0.36	0.20	0.25	0.23
	11. Plant closure	0.00	0.00	0.24	0.00	0.00	0.23	0.23	0.23	0.24	0.23	0.29	0.22	0.24	0.32	0.33	0.00	0.32	0.24	0.22	0.21
	12. Supply decrease	0.00	0.00	0.26	0.00	0.00	0.26	0.25	0.25	0.26	0.25	0.26	0.26	0.26	0.35	0.36	0.34	0.00	0.27	0.25	0.26
4) Factor 3	13. Power outage	0.00	0.00	0.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00
5) Factor 4	14. Capacity shortage	0.00	0.00	0.00	0.00	0.56	0.54	0.56	0.53	0.53	0.55	0.00	0.55	0.51	0.51	0.55	0.53	0.51	0.32	0.00	1.00
	15. Component shortage	0.00	0.00	0.00	0.00	0.44	0.46	0.44	0.47	0.47	0.45	0.00	0.45	0.49	0.49	0.45	0.47	0.49	0.68	1.00	0.00

TABLE 5: WEIGHTED SUPER-MATRIX

		0) Goal	1) Factors				2) Factor 1								3) Factor 2				4) Factor	5) Factor 4	
		Resource	Factor 1	Factor 2	Factor 3	Factor 4	1. Capaci	2. Equipm	3. Patent (	4. Plant o	5. Produc	6. Resear	7. Supply	8. Transp	9. Asseml	10. Capac	11. Plant (	12. Suppl	13. Power	14. Capac	15. Comp
0) Goal	Resource limit index	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1) Factors	Factor 1	0.53086	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Factor 2	0.27161	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Factor 3	0.09877	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Factor 4	0.09877	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2) Factor 1	1. Capacity increase	0	0.12769	0	0	0	0	0.05897	0.0578	0.05922	0.059	0.07483	0.0613	0.05767	0.0477	0.04708	0.04534	0.04644	0.05792	0.03484	0.03469
	2. Equipment failure	0	0.11539	0	0	0	0.05475	0	0.05436	0.05372	0.05272	0.06735	0.05504	0.05489	0.04282	0.04275	0.04247	0.04227	0.0531	0.02993	0.02717
	3. Patent disputes	0	0.10923	0	0	0	0.05227	0.05294	0	0.0525	0.05272	0.06236	0.05254	0.0535	0.04228	0.04058	0.04247	0.04122	0.04344	0.03043	0.03122
	4. Plant opening	0	0.16154	0	0	0	0.06035	0.05897	0.05918	0	0.06026	0.0898	0.06005	0.05976	0.04607	0.04546	0.04534	0.04592	0.05471	0.03043	0.0318
	5. Product obsolescence	0	0.15077	0	0	0	0.05849	0.05629	0.0578	0.05861	0	0.09229	0.05817	0.05628	0.04228	0.04546	0.0442	0.04435	0.04666	0.02993	0.02891
	6. Research restrictions	0	0.08308	0	0	0	0.01867	0.01809	0.0172	0.02198	0.02322	0	0.01876	0.01807	0.01138	0.01461	0.01722	0.01409	0	0	0
	7. Supply Increase	0	0.12462	0	0	0	0.06098	0.05897	0.0578	0.05861	0.05837	0.07483	0	0.05698	0.0477	0.04654	0.04362	0.04696	0.04827	0.03484	0.03353
	8. Transportation disruption	0	0.12769	0	0	0	0.05164	0.05294	0.05299	0.0525	0.05084	0.06485	0.05129	0	0.0412	0.03896	0.04075	0.04018	0.05953	0.02699	0.03007
3) Factor 2	9. Assembly bottleneck	0	0	0.14522	0	0	0.08247	0.07886	0.07959	0.08131	0.07506	0.09474	0.08319	0.08253	0	0.11228	0.11233	0.1159	0.10464	0.06159	0.06552
	10. Capacity decrease	0	0	0.34984	0	0	0.08153	0.08784	0.08571	0.08036	0.09046	0.12181	0.0813	0.07819	0.12001	0	0.12385	0.12803	0.07325	0.05435	0.04963
	11. Plant closure	0	0	0.24092	0	0	0.07403	0.07387	0.07551	0.07557	0.0741	0.13534	0.07185	0.0771	0.11278	0.11634	0	0.11321	0.08633	0.0471	0.04566
	12. Supply decrease	0	0	0.26403	0	0	0.0834	0.08086	0.08061	0.08418	0.0818	0.12181	0.08508	0.08362	0.12435	0.12852	0.12097	0	0.09941	0.05435	0.05658
4) Factor 3	13. Power outage	0	0	0	1	0	0.14286	0.14286	0.14286	0.14286	0.14286	0	0.14286	0.14286	0.14286	0.14286	0.14286	0.14286	0	0.13044	0.13044
5) Factor 4	14. Capacity shortage	0	0	0	0	0.55556	0.09678	0.10086	0.09544	0.09463	0.09813	0	0.09828	0.09179	0.09062	0.0974	0.09475	0.09158	0.08631	0	0.43478
	15. Component shortage	0	0	0	0	0.44444	0.08179	0.07771	0.08313	0.08394	0.08044	0	0.08029	0.08678	0.08795	0.08117	0.08382	0.087	0.18642	0.43478	0

TABLE 6: FINAL IMPORTANCE WEIGHTS OF RESOURCE LIMITS INDEX.

	Resource limits variables	W_i
Factor 1	Capacity increase	0.046319
	Equipment failure	0.041821
	Patent disputes	0.040555
	Plant opening	0.045127
	Product obsolescence	0.042814
	Research restrictions	0.010355
	Supply Increase	0.044868
	Transportation disruption	0.041299
Factor 2	Assembly bottleneck	0.08049
	Capacity decrease	0.07773
	Plant closure	0.073467
	Supply decrease	0.081289
Factor 3	Power outage	0.120957
Factor 4	Capacity shortage	0.124698
	Component shortage	0.128212

4.3 Discussion

The resilience of a supply chain can be decomposed into the perspectives of capability and vulnerability, and there are a variety of factors affecting them. Instead of covering all of those components, this paper targets at analyzing the resource limits under vulnerability with an innovative data-driven approach using text data from news articles and earnings call transcripts. The proposed method is designed to capture information related to several resource limits sub-factors and discover the interrelationship among them. The final outcome is the importance weights of the sub-factors, with consideration of their correlations, and these weights can be used for resource limits index calculation of the supply chain.

The results of this study provide several insights. After normalizing the data, FA served as a clustering tool capable of calculating the pairwise correlations. The four-factor categorization (latent construct) presents a much simple representative model for "resource limits" by covering 80 % of the total variance. This means that while the model of resource limits is simplified, most of the information from the data is retained. The clustering also shows which sub-factors moves in the same direction. By conducting FA, the complex nature of the supply chain resource limits is simplified into an abstract construct, and the interrelationship among the factors that affect resource limits is revealed. As a result, firms can take advantage of this approach and tackle the supply chain vulnerability problems in smaller fractions.

The correlations among sub-factors, factor loadings, and the correlations among the clusters were further used as the input of ANP. Unlike the traditional implementation of ANP, which is using experts' subjective judgments for the input, the results of FA, quantitative derivatives from the actual data, were used. The output of ANP is the global priorities (importance weights) of the input variables, and this weighting result has taken the interrelationship of the resource limits' sub-factors into consideration. Among the importance weights results, it is clear that Power Outage, Capacity Shortage, and Component Shortage have the highest importance. The results are reasonable since these three variables directly describe the lack of resources, and others describe the movement of the resources. For example, when there is a "capacity shortage" situation, the production capacity of the company is not enough for their current operations. On the other hand, a "capacity decrease" scenario may indicate that the company is not in urgent need of capacity, and other factors might be the cause of that decrease. Similar explanations can be applied to Power Outage and Component Shortage. The importance weights can be further incorporated with the normalized document counts data to calculate the CRLI and SCRLI to quantify a firm's resource limits score and its supply chain resource limits condition considering the performance of the suppliers. The application of these two indices allows firms to optimize their supply chain configuration based on resource limits.

Despite the advantages of the proposed method, there are still several limitations. Since the analysis is based on document count data from news articles and earnings call transcripts, relatively small companies might not have sufficient data to evaluate their resource limits, as well as other elements related to supply chain resilience. An alternative approach is required for those cases. In addition, this study targets only companies in the technology sector. Different characteristics in different industries would affect the FA model, the interrelationship among sub-factors, and thus the importance weights. Other than that, the time frame of the dataset and the data record frequency would also have an impact on the model. Instead of collecting monthly data in a 15-year time frame, a daily or weekly data collection for a shorter time frame might have different outcomes.

5. CONCLUSION

This paper utilizes textual data of open access news articles and earnings call transcripts in evaluating companies' "resource limits", a sub-component of supply chain vulnerability. Automatic regular expression classifiers were developed to capture documents that are related to the 17 resource limits sub-factors. Factor analysis was conducted to reveal the latent construct of the variables and their interrelationship. The output of the factor analysis was then converted to an ANP model, and the variable importance weights were calculated. The importance weights indicated the rank of the variables, and can further aggregate into a company's resource limits index (CRLI). Finally, a target company's supply chain resource limits index (SCRLI) can be calculated by averaging the CRLIs of its critical suppliers.

The contributions of this study are as follows. Analyzing open access textual data to evaluate supply chain vulnerability can break the barriers that a company's private information is often confidential. Enterprises can obtain useful information for supply chain design by applying the proposed approach. In addition, this research takes the resource limit sub-factors' interdependence into consideration, which, mostly in the past, researchers and practitioners assumed their independence. Moreover, the resource limits scoring method (CRLI and SCRLI) provides an innovative way to rank suppliers and can further improve the supply chain configuration.

Understanding supply chain vulnerabilities has direct implications for robustness in supply chains and related product designs. Product supply chains should be reviewed periodically to monitor related vulnerabilities and investments in flexible product designs that can diversify their supply chains with minor costs.

Future research would be including other factors of vulnerability and also factors related to the capability to develop a supply chain resilience assessment framework further. The connection with supply chain resilience, design flexibility, and companies' performance should also be validated.

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