Performance Evaluation of Logistics Service Providers Under Uncertain Environment Using a rDANP-U Model

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Abstract: Due to many unexpected events, international enterprises are facing an increasing supply and demand uncertainty. From the perspective of logistics demands, selecting the appropriate logistics service providers is an important issue. From the perspective of logistics service providers, satisfying customers' needs in competitive markets is vital. This study focuses on three multinational logistics companies providing services in China, Hong Kong, and Taiwan as case studies for investigating the selection criteria in the context of logistics service providers and for evaluating their performance in an uncertain market. The criteria with a higher total influence and net influence should receive a higher weight than other criteria. However, the existing modified DANP-mV model that integrates the DEMATEL (Decision-Making Trial and Evaluation Laboratory) method, the ANP (Analytic Network Process) method, and the mVIKOR (modified Vlsekriterijumska Optimizacija I Kompromisno Resenje) method often does not follow this logic. This study proposes a new model called rDANP-U (revised DANP with mean group Utility) with the purpose of generating more proper weights for the selection criteria with a higher total influence and net influence. Further on, the mean group utility component derived from the VIKOR method is employed for evaluating the performance of the three chosen logistics service providers operating in an uncertain environment and for providing improvement strategies for them.

Keywords: Logistics Service Providers, MCDM, DEMATEL, DANP, VIKOR, r-DANP-U.

1. Introduction

2020 has been a tumultuous year for the world. The new coronavirus (Coronavirus Disease 2019, COVID-19) that appeared in late 2019 spread worldwide in early 2020. Most countries have implemented restrictive measures and closed borders, resulting in a sharp drop in global international trade. Not only COVID-19, but the US-China trade tariff war, natural disasters, and artificial disruptions also affect global trade. One of the areas affected directly is logistics. Since logistics plays a vital role in the circulation of national and international trade, its importance even affects the development and competitiveness of a country. In this uncertain market, global logistics service providers (LSPs) must face the strategic choice of business interests and risks (Sabbagh, 2021).

LSPs generally provide various logistic services and real-time operational information feedback based on customer needs. LSPs are external suppliers of companies. The critical competitive factors of enterprises arise from the close cooperative relationship between enterprises and external suppliers and the circulation of product information, such as product quality, specifications, price/cost etc. Close cooperation between companies and external suppliers can reduce costs and increase price competitiveness to create a competitive position on the market. Taherdoost & Brard (2019) pointed out that two critical issues exist in supplier selection: one is the selection of evaluation criteria and the other is choosing the appropriate method to facilitate the selection process.

Traditionally, LSP selection and evaluation have focused on price/cost, service quality, logistics specialty, and LSP demand compatibility. Since COVID-19, LSPs have been facing more risks, such as uncertain changes in market demands, supplier competition, changes in the flow of products, etc. One example is that LSPs cannot be on time due to traffic restrictions (Liu et al., 2022) and must deal with unforeseen market changes in the future. More criteria must be assessed, and LSPs are now more cautious when formulating their competitive strategies. Environmental variables have played an essential role in company strategies and performance in the past; therefore, these variables should be investigated and evaluated when making decisions.

This study considers LSPs that provide services in China, Hong Kong, and Taiwan. Due to cross-strait trade between China and Taiwan, the scope of the research includes general sea and air import and export cargo business, excluding express

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logistics. Existing research on selection criteria for LSPs appears to be distributed, requires a comprehensive and systematic understanding, and fails to identify key differences and vital causal relationships between these criteria.

Many studies may not generate the correct weights as intended. For example, the modified DANP-mV model that integrates the DEMATEL, the ANP, and the mVIKOR methods in studies of Qu et al. (2019) often gives a smaller weight to the criteria with a higher total influence and net influence than to the criteria with a lower total influence and net influence. In other words, the final weights of the modified DANP-mV model are inconsistent with the influence relationship results for DEMATEL. This phenomenon is also presented in some studies of DANP (Chiu, Tzeng & Li, 2013; Gigović et al., 2017; Hsu, Liou & Chuang, 2013; Shen, Yan & Tzeng, 2014). It leads to unintuitive and unreasonable results. Therefore, this study revises this model to generate proper, consistent weights and implications. In a practical sense, it makes a big difference since resource dislocation can be avoided.

The framework of this study is different from the previous LSP assessment framework because this study incorporates the characteristics of uncertain criteria into the assessment. The research results indicate that when market competition is uncertain, service providers can no longer use the previously stable market supply and demand standards to measure service quality. Currently, LSPs can only meet the customer demand through the flexibility and quick response of the service model and meet the customer expectations for service quality.

This study has three benefits. First, it revises the framework proposed by Qu et al. (2019) and provides a proper framework that generates correct weights in comparison with other methods. Second, the selection criteria are determined, defined, and analysed in response to the sudden shock of COVID-19 and the ongoing changes in the competitive market under uncertainty. Lastly, this study uses a revised LSP assessment framework to investigate the relationship between different selection criteria in COVID-19 and post-COVID-19 periods. The obtained results can help companies better understand the environment, make informed decisions, or create and maintain competitiveness.

The remainder of this study is organized as follows. Section 2 reviews relevant studies for the selection of LSPs. Section 3 describes the details of the proposed revised framework. Further on, in Section 4 three cases of logistics companies providing shipping services in China, Hong Kong and Taiwan are analysed using the revised framework. Finally, Section 5 concludes this paper and outlines possible future research directions.

2. Literature Review

2.1 Logistics Service Providers

This study examines the current logistics service practices during the COVID-19 pandemic and after COVID-19 by reviewing the relevant literature on the logistics supply chain from 2020 to 2022. Since COVID-19 started, dealing with uncertainty was essential for all companies. The criteria used to assess LSPs changed drastically. For example, Luyen & Van Thanh (2022) investigated the evaluation and selection of the LSPs. However, their criteria are not supported by the literature. An extensive literature review is conducted on the LSP selection criteria. Then, requirements related to the logistics capabilities of LSPs under an uncertain environment were collected through in-depth interviews with management executives of three multinational logistics companies. After removing some criteria in the context of semantic duplication by interviewing the focus experts, 31 criteria were obtained.

Based on the preliminary data of 31 criteria, 14 experts familiar with logistics operations were interviewed to provide advice and reach a consensus on the selection criteria for the LSPs by the modified Delphi method. Finally, 18 criteria were selected and classified according to relevant attributes, as it is shown in Table 1. The assessment structure includes five dimensions: Operation Management (D_1), Price/Cost (D_2), Logistics Service Capabilities (D_3), Flexibility (D_4), and Customer Satisfaction (D_5) .

2.2 Work Related to Logistics Service Providers

With the gradual popularization of the circular economy, companies have considered logistics efficiency and environmental protection when choosing a logistics service provider to achieve sustainable development. Gupta, Singh & Mangla

Table 1. Evaluation criteria of logistics service providers

Dimension	Criteria	References
Operation Management (D_1)	Financial Stability (C_{11})	Hofmann et al. (2018)
	Service Quality Management (C_{12})	Wasielewska-Marszalkowska (2021)
	Informatization Level (C_{13})	Grawe & Ralston (2019), Gupta, Singh & Mangla (2021)
	Green Images (C_{14})	Sallnäs & Huge-Brodin (2018), Sallnäs & Björklund (2020)
Price/Cost (D_2)	Logistics Service Handling Charge (C_{21})	Hofmann et al. (2018)
	Transportation Price/Cost (C_{22})	Du et al. (2018), Oláh et al. (2018)
	Warehouse Price/Cost (C_{23})	Agyabeng-Mensah et al. (2020)
Logistics Service Capabilities (D_3)	Logistics Specialty and Demand Compatibility (C_{31})	Narkhede et al. (2017)
	Adaptability to Customer Dynamic Requirements (C_{32})	Grawe & Ralston (2019)
	Dynamic Cargo Tracking (C_{33})	Karia (2018), Gupta, Singh & Mangla (2021)
	Control of Transportation Resources (C_{34})	Darkow, Weidmann & Lorentz (2015)
Flexibility (D_4)	Service Model Flexibility (C_{41})	Liu & Lee (2018)
	Provision of Value-Added Service (C_{42})	Rivera, Sheffi & Knoppen (2016), Mathauer & Hofmann (2019)
	Responsiveness to Target Market (C_{43})	Wetzel & Hofmann (2020)
Customer Satisfaction (D_5)	Reputation and Experience (C_{51})	Govindan, Khodaverdi & Vafadarnikjoo (2016)
	Reliability (C_{52})	Serbetcioglu & Göçer (2020), Chakuu, Masi & Godsell (2020)
	Reactivity (C_{53})	Ramezani, Bashiri & Tavakkoli-Moghaddam (2013), Fallahpour et al. (2021)
	Operation Safety (C_{54})	Gupta, Singh & Mangla (2021)

(2021) pointed out that selecting the right LSP can significantly affect supply chain's performance in terms of sustainability indicators. Their study collected data from 150 LSP customers. The data was analyzed by factor analysis, and five criteria were obtained. Then, Analytic Hierarchy Process (AHP) and Fuzzy Technique for Order Preference were used to select the best LSPs for sustainable service quality.

Jovčić et al. (2019) used fuzzy AHP to discuss criteria decision-makers should consider for third-party logistics (3PL) providers and their evaluation. The assumption that all selection criteria were equally important rarely holds. They evaluated selection criteria and identified priorities to help policymakers. 3PL operation scheduling involves many uncertain criteria, such as shipping speed, weather, and 3PL's capability. Fuzzy evaluation is easily affected by the subjectivity of decision markers, which may cause the results of 3PL scheduling to deviate from the actual situation (Banomyong et al., 2022). Furthermore, fuzzy AHP assumes that assessment results are accurate and conform to the normal distribution. However, this assumption may not hold in practice. For example, evaluators may be affected by subjective criteria, personal experience, and time constraints, resulting in biased or inconsistent evaluation results (Chen, 2000; Chen et al., 2011).

One of the well-known methods to select logistics providers is ANP. Tavana et al. (2016), Ocampo et al. (2019), Huang, Tan & Guan (2021), and Orji et al. (2020) used ANP to evaluate logistics providers. ANP is commonly used in combination with various methods. One such method is used for training and verifying radial basis function (RBF) neural networks, as discussed in (Huang, Tan & Guan, 2021). The above method is used to evaluate cruise logistics service providers. The study emphasizes that this method can avoid the impact of subjective criteria and enhance evaluation dynamics. The RBF method is effective in mathematical modeling and solving problems such as function classification and clustering. However, the RBF method is sensitive to the number and distribution of data sets and is prone to over-fitting.

Another well-known method is DEMATEL. Yuan, Xu & Zhang (2022) determined criteria and used DEMATEL to investigate the relationships between them to choose suitable third-party service providers. Combining fuzzy DEMATEL with the Delphi method, Mangla et al. (2018) could benchmark the implementation of logistics management. Reverse logistics was also investigated using DEMATEL or DEMATEL with other methods by Ocampo et al. (2019).

DEMATEL based on ANP (DANP) is used extensively to understand and analyze the cause-and-effect relationship between criteria (Radulescu, Boncea & Vevera, 2023). For example, Jiang et al. (2019) used DANP to identify interactions between manufacturing and logistics industries in China, Kim, Ramkumar & Subramanian (2019) discussed preparation for a disaster, Oláh et al. (2018) examined the developments in information technology and their effect on LSP's financial performance, and Sufiyan et al. (2019) evaluated the food chain's performance. Recently, Chang, Chiu & Wang (2020), Li, Diabat & Lu (2020), and Sarabi & Darestani (2021) adopted DANP to conduct research on supplier selection.

As mentioned in Section 1, modified DANP-mV and DANP models sometimes assign improper weights to criteria with higher total influence and net fluence. Preliminary experiments were conducted and it was found that the way of normalizing the total-influence relationship matrix proposed by Yang & Tzeng (2011) can avoid this phenomenon. Furthermore, when the number of criteria increases n times, the number of pairwise criteria increases $n(n-1)$ times, which requires more time and resources to conduct the research. To better handle more complex problems, this study adopted the segregation method used by Qu et al. (2019). In comparison with the method of Qu et al. (2019), which uses the total sum of each row to normalize the total-influence relationship matrix, this study uses the total sum of each column to normalize. The revised method called rDANP can generate weights more accurately than the method of Qu et al. (2019).

The VIKOR method is used to compromise the solution of experts or the weights (Wang et al., 2021). Chiu, Tzeng & Li (2013) proposed the DANP-V method combining VIKOR with DANP. VIKOR considers a compromise solution and weight stability intervals with the initial weights (Opricovic & Tzeng, 2004). VIKOR may not align well with DANP since DANP considers the problem of interdependence of criteria and feedback. Therefore, this study adopts only the "mean group utility" of VIKOR to calculate the gaps between the worst and best solutions.

In summary, this study combines rDANP and mean group Utility, which is called rDANP-U, to investigate the selection criteria for Logistics Service Providers. The rDANP-U model retains the advantages of solving large, complex problems used by Qu et al. (2019), uses the normalisation method proposed by Yang & Tzeng (2011) and considers the mean utility of the group. Taking into account practice and applications, the revised rDANP-U model avoids misallocation of resources and better demonstrates the relationship between selection criteria than the existing methods.

3. Methodology

The symbols and definitions used in this study are described in Table 2.

Table 2. Definition of symbols

Symbol	Definition
A	Average Direct-Relation Matrix
D	Degree of being Influenced
E	Initial Direct-Relation Matrix
F	Performance Evaluation Matrix
H	Number of Experts
N	Normalized Direct-Relation Matrix
R	Degree of Influence
$R+D$	Total Degree of Influence
$R-D$	Degree of Net Influence
S_k	Average Group Utility
T	Total-Relation Matrix
P	Normalized Total-Relation Matrix
W_c^g	Global Influence Weight of Criterion c
W_d	Weight of Dimension d
$W_{d_c}^l$	Local Weight of Criterion c within Dimension d
f^{asp}	Aspiration Value
f^{wst}	Worst Value
q	Number of Alternative Plans
f_{qj}	Performance Value of Alternative q on Criterion j
r_{qj}	Normalized gap of f_{qj} to the aspiration and worst values

The proposed rDANP-U model consists of the following 13 steps.

Step 1: Form initial direct-relation matrix E^h

Matrix E^h is a nonnegative $n×n$ matrix formed by pairwise comparisons between two criteria. Each expert $h \in H$ specifies a level ε_{ij}^h that indicates the impact of criterion *i* on criterion *j* based on the employed modified DEMATEL questionnaire. Matrix E^h can be expressed as equation (1):

$$E^h = \begin{bmatrix} \varepsilon_{11}^h & \cdots & \varepsilon_{1j}^h & \cdots & \varepsilon_{1n}^h \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon_{i1}^h & \cdots & \varepsilon_{ij}^h & \cdots & \varepsilon_{in}^h \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon_{n1}^h & \cdots & \varepsilon_{nj}^h & \cdots & \varepsilon_{nn}^h \end{bmatrix} \quad (1)$$

Step 2: Calculate the average direct-relation matrix A

Matrix *A* can be calculated through the average score $a_{ij} = \frac{1}{H}\sum_{h=1}^{H} \varepsilon_{ij}^h$ and it is expressed in equation (2):

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \quad (2)$$

Step 3: Examine the consistency of expert assessments

To avoid the contradiction of the expert's own opinion, the consistency of the expert's assessments is determined by equation (3).

$$consistency = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{\left| a_{ij}^H - a_{ij}^{H-1} \right|}{a_{ij}^H} \right) \times 100\% \quad (3)$$

This study adopts a threshold of 0.05 which is frequently used in the literature.

Step 4: Normalize the average direct-relation matrix A

The normalized matrix *N* is obtained by using equations (4) and (5):

$$N = \mu A \quad (4)$$

$$\mu = min\left\{ \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max\limits_{1 \le j \le n} \sum_{i=1}^{n} a_{ij}} \right\} \quad (5)$$

Step 5: Derive the total-relation matrix T

Matrix *T* is computed by summing up the matrices of relation in the infinite period of time $N^2,..., N^\infty$ and is defined in equation (6):

$$\begin{aligned} T &= N + N^2 + \ldots + N^z \\ &= N(1-N)^{-1} \quad \text{when} \quad z \to \infty \\ &= \left(t_{ij}\right)_{n \times n} \end{aligned} \quad (6)$$

Step 6: Analyse the results and plot the influential network relationship map INRM

To plot the INRM, the sums of each row R_i and each column D_j of the total-relation matrix *T* are calculated using equations (7) and (8):

$$R = \left(R_i\right)_{n \times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n \times 1} \quad (7)$$

$$D = \left(D_j\right)_{n \times 1} = \left(D_j\right)'_{1 \times n} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1 \times n} \quad (8)$$

Step 7: Normalize the total-relation matrix T

Instead of using total sums of each row (Qu et al., 2019), this study uses the total sum of each column to normalize the total-relation matrix *T*. The normalized matrix *P* can be achieved using equation (9):

$$P = (p_{ij})_{n \times n} \quad \text{where} \quad p_{ij} = \frac{t_{ij}}{D_j} \quad (9)$$

Step 8: Obtain weights W_d of dimension d and local weight $W_{d_c}^l$ of criterion c within dimension d

Matrix *P* is multiplied by itself multiple times in equation (10) until it converges to matrix *W*. It becomes a stable matrix *W* when the power of *P* is raised to infinity.

$$W = \lim_{z \to \infty} \left(P\right)^z \quad (10)$$

As mentioned earlier, this study adopted the segregation method used by Qu et al. (2019). The normalized total-relation matrices between dimensions and between criteria within dimensions are separated, then equation (10) is applied to get the weight W_d of dimension *d* and the local weight $W_{d_c}^l$ of criterion *c* within dimension *d.*

Step 9: Compute global influence weights of all criteria

The global weight W_c^g of criterion *c* is calculated by multiplying the weight of dimension W_d with the local weight of criteria $W_{d_c}^{l}$ in that dimension as expressed in equation (11):

$$W_c^g = W_{d_c}^l \times W_d \tag{11}$$

Step 10: Establish a performance evaluation matrix F

The matrix F is extracted and established from the database and shown in equation (12):

$$F = \begin{array}{c} \\ a_1 \\ \vdots \\ a_i \\ \vdots \\ a_q \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{bmatrix} f_{11} & \cdots & f_{1j} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ f_{ij} & \cdots & f_{ij} & \cdots & f_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ f_{q1} & \cdots & f_{qj} & \cdots & f_{qn} \end{bmatrix} \end{array} \tag{12}$$

Step 11: Derive aspiration value and the worst value

The aspiration and worst values of n criteria are represented as f^{asp} and f^{wst}, respectively. This study rates performance from 0 to 100, with 0 being poor and 100 good. Therefore, f^{asp} is 100, and f^{wst} is 0.

Step 12: Normalize the effects of alternatives and calculate the gap to the best value for each criterion

The gap r_{qj} of criterion j between the performance value and the aspiration value for each criterion is calculated in equation (13):

$$r_{qj} = \frac{\left| f^{asp} - f_{qj} \right|}{\left| f^{asp} - f^{wst} \right|} \tag{13}$$

Step 13: Evaluate alternatives' performance

Mean group utility and degree of maximum regret are two components of standard VIKOR. Since the revised rDANP-U model focusses on alternatives' performance, this model uses only the average group utility S_k which can be computed by equation (14):

$$S_k = \sum_{j=1}^{n} W_c^g r_{qj} \tag{14}$$

4. Results

4.1 Data Collection

The aim of this study is to investigate the LSP selection criteria in an uncertain environment and analyze the importance of those criteria. 14 chief operating officers of LSPs and logistics service demanders (LSDs) in the industry were interviewed using the modified Delphi method. The experts were from mainland China, Hong Kong, Taiwan, and Japan. Approximately 80% of the interviewees had 35-40 years of practical experience directly related to logistics.

This study uses the modified DEMATEL questionnaire by Qu et al. (2019) to reduce the complexity of pairwise comparisons between all criteria. Data comes from expert questionnaires with a rating scale of 0 (no influence) to 4 (high influence). Then, the weights of all dimensions and the weights of criteria within each dimension are subsequently derived according to the procedure described in the previous section.

To demonstrate the effectiveness of the revised VIKOR in selecting LSPs in an uncertain environment, this study evaluates three LSP company cases (S company, D company, and K company) located in mainland China where the COVID-19 virus outbreak occurred. These three companies are funded by Taiwan, Hong Kong, and China, respectively. Here, the top ten customers of the business logistics service of S company are invited to conduct a performance evaluation on the three LSPs.

4.2 Results and Discussion

According to the calculation process described in Section 3, Figure 1 illustrates the influential network relationship map to demonstrate the total effects of the dimensions and criteria.

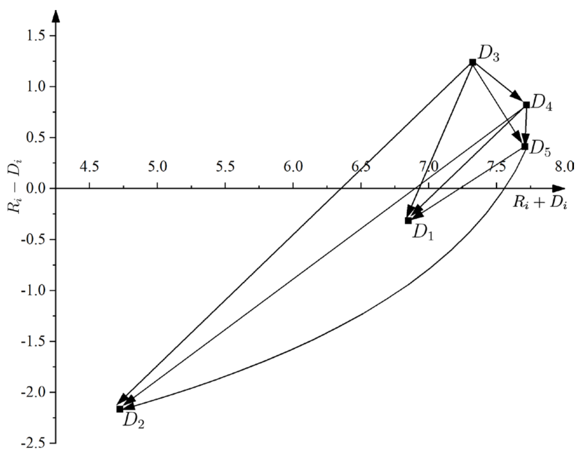

Figure 1. Influential network relationship between dimensions

As it can be seen in Figure 1, each of the dimensions D_3, D_4, and D_5 has a positive value on $R - D$ and can be classified as a cause. On the other hand, D_1 and D_2 are classified as affected factors. Operation Management (D_1) and Price/Cost (D_2) are effects that are influenced by Logistics Service Capabilities (D_3), and Flexibility (D_4), and Customer Satisfaction (D_5). If the same amount of effort is allocated to each criterion, D_3 will have the largest net effect on the system, followed by D_4 and subsequently D_5.

Figures 2 to 6 indicate that criteria C_{11}, C_{13}, C_{22}, C_{23}, C_{33}, C_{34}, C_{42}, C_{43}, C_{52}, and C_{54} are classified as causes, while other criteria such as C_{12}, C_{14}, C_{21}, C_{31}, C_{32}, C_{41}, C_{51}, and C_{53} are classified as effects. However, it does not mean that enterprises do not spend effort on the dimensions/criteria of low importance. If stakeholders do not maintain the respective dimensions/criteria, there may be no other factors to maintain the system, and the final results can be distorted.

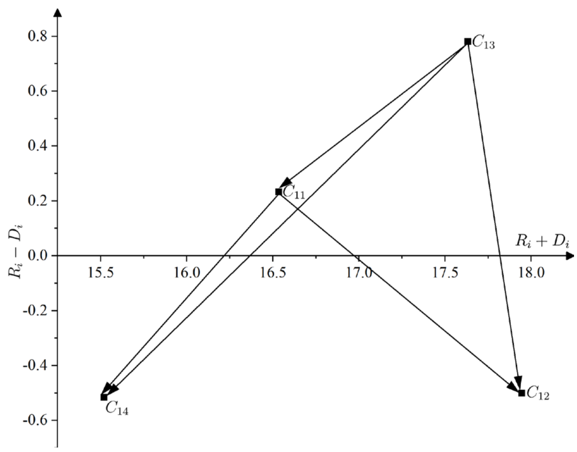

Figure 2. Influential network relationship within D_1

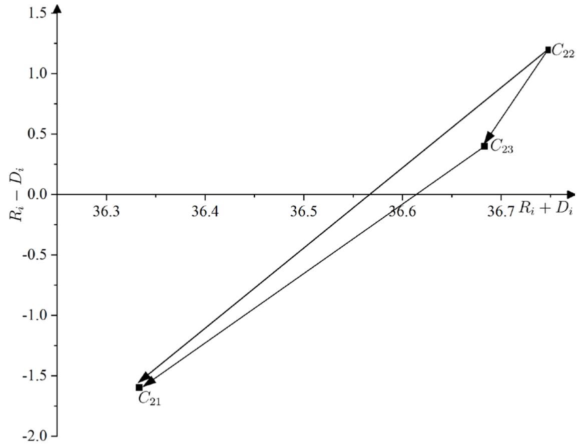

Figure 3. Influential network relationship within D_2

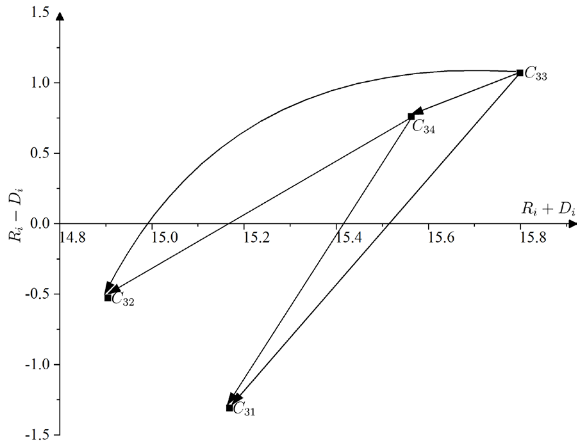

Figure 4. Influential network relationship within D_3

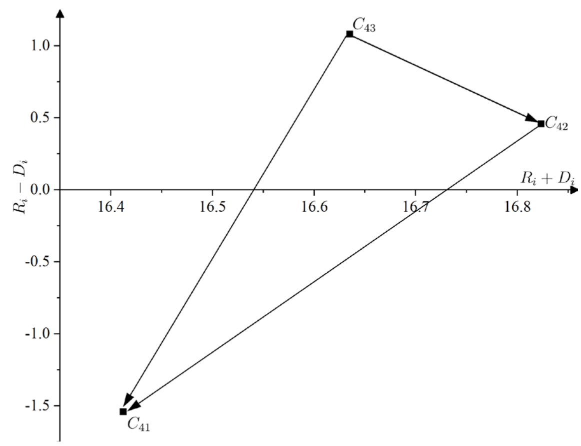

Figure 5. Influential network relationship within D_4

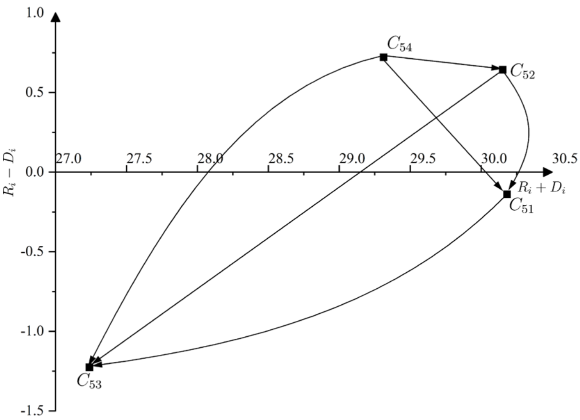

Figure 6. Influential network relationship within D_5

Combining the calculated weights and the performance evaluation conducted by customers, Table 3 displays the performance and gap evaluation for the three company cases. Cases S, K, and D are sorted by ascending order of the value of the total gap, with preference from the lowest to the highest. Case S has the minimum gap in dimensions D_5, D_1, and D_2. Although case D has the largest overall gap, it has the most competitive price/cost dimension (D_2) which

Table 3. The global weights and the ranking of the criteria related to the performance and gap evaluation for the three chosen company cases

	Global weight	Rank	Performance			Gap		
			Case S	Case D	Case K	Case S	Case D	Case K
Operation Management (D_1)	0.194					0.241	0.520	0.237
Financial Stability (C_{11})	0.048	14	70	40	70	0.3	0.6	0.3
Service Quality Management (C_{12})	0.050	13	72.5	41	72	0.275	0.59	0.280
Informatization Level (C_{13})	0.053	11	73	40	75	0.27	0.6	0.25
Green Images (C_{14})	0.043	15	90	75	90	0.1	0.25	0.1
Price/Cost (D_2)	0.077					0.314	0.311	0.359
Logistics Service Handling Charge (C_{21})	0.024	18	61	73	56	0.39	0.27	0.44
Transportation Price/Cost (C_{22})	0.026	16	85	65	80	0.15	0.35	0.2
Warehouse Price/Cost (C_{23})	0.026	17	59	69	55.5	0.41	0.31	0.445
Logistics Service Capabilities (D_3)	0.246					0.282	0.658	0.442
Logistics Specialty and Demand Compatibility (C_{31})	0.056	10	70	40	60	0.3	0.6	0.4
Adaptability to Dynamic Customer Requirements (C_{32})	0.058	9	72	32.5	53.5	0.28	0.675	0.465
Dynamic Cargo Tracking (C_{33})	0.067	4	70	30	60	0.3	0.7	0.4
Control of Transportation Resources (C_{34})	0.065	5	75	35	50	0.25	0.65	0.5
Flexibility (D_4)	0.247					0.233	0.420	0.331
Service Model Flexibility (C_{41})	0.074	3	75	30	60	0.25	0.7	0.4
Provision of Value-Added Service (C_{42})	0.086	2	90	65	85	0.1	0.35	0.15
Responsiveness to Target Market (C_{43})	0.087	1	65	75	55	0.35	0.25	0.45
Customer Satisfaction (D_5)	0.236					0.277	0.598	0.332
Reputation and Experience (C_{51})	0.061	7	70	50	70	0.3	0.5	0.3
Reliability (C_{52})	0.062	6	71.5	38	70	0.285	0.62	0.3
Reactivity (C_{53})	0.053	12	75	33.5	53.5	0.25	0.665	0.465
Operation Safety (C_{54})	0.061	8	73	38.5	72	0.27	0.615	0.28
Overall gap						0.263	0.532	0.342
Rank						1	3	2

contains low-importance criteria. Case K has the minimum gap in Operation Management (D_1). For dimensions D_2, D_3, D_4, and D_5, case K has a similar level of gap, which means case K tries to pursue balance in each dimension except for Operation Management (D_1).

All three cases feature a good performance for Green Images (C_{14}) and Provision of Value-Added Service (C_{42}). For each criterion, Case S has the largest three gaps in Responsiveness to Target Market (C_{43}), Logistics Service Handling Charge (C_{21}), and Warehouse Price/Cost (C_{23}). Case D has many criteria that can be improved, especially Service Model Flexibility (C_{41}), which has a high global weight. Case D implemented criteria C_{21}, C_{22}, C_{23}, C_{42}, C_{43} very well in relation to other criteria by Case D. Case K needs to improve the performance of criteria that have high global weights and large gaps such as

Dynamic Cargo tracking (C_{33}), Control of Transportation Resources (C_{34}), Service Model Flexibility (C_{41}), and Responsiveness to Target Market (C_{43}).

In general, performance evaluation results help customers understand the strengths and weaknesses of LSPs and then select an appropriate third-party LSP. The analytical results suggest that each case allocates limited resources to improve critical factors.

5. Conclusion

There are always two critical aspects when choosing a logistics supplier. One is related to the selection criteria, and the other to the appropriate method that can improve the selection process. With regard to the selection of LSPs in an uncertain environment, such as the COVID-19 situation, this study conducted a comprehensive review of the literature and interviews with industry experts were conducted in order to determine the essential selection criteria. Afterwards, the proposed rDANP-U model which is a hybrid MCDM research model determined the importance of selection criteria and analysed the relationships between all employed dimensions and the criteria of each dimension. The revised model differs from the previous models since causes are assigned higher weights than effects, which is more appropriate according to their influence and importance. The mean group utility is adopted to rank alternatives for LSP customers. Moreover, analytical results can also improve strategies and recommendations for LSPs.

The obtained results showed that based on empirical evidence, the dimension of Logistics Service Capabilities (D_3) and the dimension of Flexibility (D_4) are the two most important dimensions, followed by the dimension of Customer Satisfaction (D_5). Customers require the LSPs to adapt their plans when the market environment is uncertain. Besides, LSPs can improve Operation Management (D_1) and Price/ Cost (D_2) to complement their competitive advantages and raise customer satisfaction.

Since this study is based on interviews with industry experts from international LSPs funded by Taiwan, Hong Kong and China, the analytical results may not be applicable in other countries. Extensive research should be conducted involving LSPs in other areas so as to obtain more comprehensive results. Additionally, there are potential interactions between the criteria of different dimensions. Future studies could also investigate those interactions.

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