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Finding Outlier by using a modified Hybrid Model with the integration of DEMATEL and DANP techniques, and combining the Cluster Analysis

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***Abstract*—A hybrid model (in this paper we call it D-DANP) with the integration of DEMATEL (Decision-Making Trial and Evaluation Laboratory) and DANP (DEMATEL-base ANP) techniques is a popular and effective tool which can output some visual maps to summarize those complex human thinking by its systematization method, and provide some vital information to decision maker. D-DANP model uses questionnaire to collect raw data from expert. Therefore, the most important thing is to collect effective and reliable sample by confirming the quality of the expert.**

The D-DANP uses the function of consistence examination to verify the reliability of raw data which can influence the outcome of INRM directly and disturb the interpretation of result. However, the D-DANP can not provide the more reliable INRM without finding the outlier form raw data. This paper intends to propose a new modified hybrid model based on the D-DANP model, to develop trustworthy INRM by eliminating outlier which can be found by cluster analysis technique according to influential weight result. And this paper will illustrate in some circumstance the raw data (with outlier) pass the consistence examination, while the INRM appearing an inaccurate condition. The appraisal system of B&B (Bed and Breakfast) will be used to demonstrate how to apply the new modified hybrid model to find out the outlier.

Keywords—*D-DANP model, raw data, reliability, INRM, appraisal system of B&B, new modified hybrid model*

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I. Introduction

A hybrid model with the integration of DEMATEL (Decision-Making Trial and Evaluation Laboratory) and DANP (DEMATEL-base ANP) techniques was presented in 2008 [12]. This hybrid model (in this paper we call it D-DANP) is a popular and effective tool which can output some visual maps to summarize those complex human thinking by its systematization method, and provide some vital information to decision maker. In another word, this D-DANP model was created to solve real problem, by interpreting the outcomes of INRM (Influence network relation map) and influential weight [2, 12]. Thus, the D-DANP is suitable for dealing with those “selecting”, “evaluation” and “devising” practical issues.

This D-DANP model uses questionnaire to collect raw data from expert. Expert system is very different from the traditional statistic. Traditional statistic is focus on inference, and it requests a sufficient amount of effective samples to meet the central limit theorem. However, the expert system pays more attention about how to make decision via expert’s experience, and value the expert quality much more than its number. And the most important thing of expert system is to collect effective and reliable sample by confirming the quality of the expert.

The D-DANP uses the function of consistence examination to verify the reliability of raw data which can influence the outcome of INRM directly and disturb the interpretation of result. However, this paper will show below that this function in D-DANP can not guarantee the reliability of raw data even pass the examination. Since this function can not precisely identify the outlier from raw data in some circumstances. Therefore, the D-DANP can not provide the more reliable INRM without finding the outlier form raw data.

This paper intends to propose a new modified hybrid model based on the D-DANP model, to develop trustworthy INRM by eliminating outlier which can be found by cluster analysis technique according to influential weight result. And this paper will illustrate in some circumstance the raw data (with outlier) pass the consistence examination, while the INRM appearing an inaccurate condition. The appraisal system of B&B (Bed and Breakfast) will be used to demonstrate how to apply the new modified hybrid model to find out the outlier.

II. The procedure and development of hybrid model and problem description

D-DANP model is a kind of hybrid model with the integration of DEMATEL (Decision-Making Trial and Evaluation Laboratory), which was proposed in 2008 [12]. D-DANP is a popular and effective tool which can output some visual maps to summarize those complex human thinking by its systematization method, and provide some vital information to help decision maker out of the problem [4]. Further more, this model is very suitable for practical issues, hence, this method has been used in a wide range of social sciences areas [2, 3, 5, 6].

D-DANP model consists of two methods were made. The first one was presented in 1972, we called it DEMATEL (Decision-Making Trial and Evaluation Laboratory) [1]. DEMATEL is to investigate the relationship between factors interact with each other, and using visual approach to present research findings. Thus, the result of DEMATEL will be the fist analysis tool——INRM, which can apply to many academic and practical fields [7, 10, 11]. The second analysis method is IW, which come form DANP model by using Satty's Analytical Hierarchy Process [8] as Fig 1 showing below.

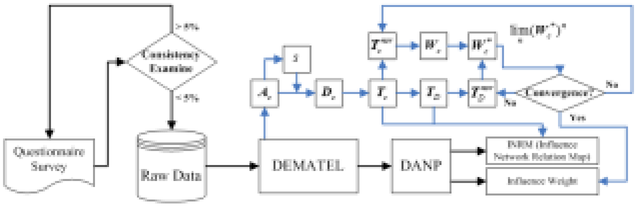


Fig. 1 Traditional DANP Method Procedure [12]

Hereinafter, the study will give an example to illustrate the issue we discussed above. First, we will use three indicators (A, B, C) to establish 10 samples (as shown in Table 1).

Table 1. Initial Influence Matrix of 10 samples

1	**A**	**B**	**C**	**2**	**A**	**B**	**C**	**3**	**A**	**B**	**C**	**4**	**A**	**B**	**C**	**5**	**A**	**B**	**C**
A	0	2	3	**A**	0	0	3	**A**	0	3	2	**A**	0	3	2	**A**	0	3	2
B	1	0	2	**B**	3	0	2	**B**	0	0	1	**B**	3	0	1	**B**	3	0	1
C	4	2	0	**C**	2	3	0	**C**	2	3	0	**C**	4	2	0	**C**	3	2	0
6	**A**	**B**	**C**	**7**	**A**	**B**	**C**	**8**	**A**	**B**	**C**	**9**	**A**	**B**	**C**	**10**	**A**	**B**	**C**
A	0	3	2	**A**	0	2	4	**A**	0	2	3	**A**	0	2	3	**A**	0	2	3
B	2	0	2	**B**	2	0	1	**B**	2	0	1	**B**	2	0	1	**B**	2	0	1
C	2	1	0	**C**	2	2	0	**C**	2	2	0	**C**	2	2	0	**C**	1	2	0

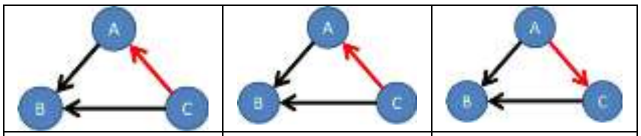
Based on the original D-DANP mode, the first 8 samples show the consistency of the verification value staying at 0.02, even adding the sample 9 and 10 the consistency test results are also far below 0.05. According to the original D-DANP mode setting, its output of the analysis tool (INRM) will be stable, and no more change in this situation.

However, as shown in Table 2 and Figure 2 ($\boldsymbol{T}_8$ representing the matrix of overall impact of relationship of the 8 samples, $\boldsymbol{T}_9$ representing the matrix of overall impact of relationship of the 9 samples, $\boldsymbol{T}_{10}$ representing the matrix of overall impact of relationship of the 10 samples), we can find out that *C* will influence *A* and *B* which also influenced by *A*, from the first 8 samples' INRM. Although adding the sample 9 cannot alter the structure of the INRM, adding the sample 10 changed the whole result that *A* will influence *C* and *B* which influenced by *C* as well.

As the INRM is an important analytical tool for the follow-up discovery. A more reliable INRM is very necessity. But the original INRM method can not distinguish some outliers from the original materials, in some cases. So, the research will focus on discovering those outliers and developing a more reliable INRM method.

Table 2. Total Influence Matrix of T8, T9, T10

T_8	A	B	C	T_9	A	B	C	T_{10}	A	B	C
A	2.79	**3.01**	2.89	**A**	2.53	**2.76**	2.68	**A**	2.18	**2.46**	**2.41**
B	2.43	2.07	2.17	**B**	2.21	1.86	1.98	**B**	1.93	1.62	1.76
C	**3.10**	**2.96**	2.5	**C**	**2.8**	**2.68**	2.26	**C**	2.39	**2.33**	1.93



INRM of $\boldsymbol{T_8}$ | INRM of $\boldsymbol{T_9}$ | INRM of $\boldsymbol{T_{10}}$

Fig 2. The INRM of $\boldsymbol{T_8}$, $\boldsymbol{T_9}$, $\boldsymbol{T_{10}}$

III. The modified hybrid model with DEMATEL and DANP

This section will describe what New DANP method is and how to use it. Thus, we separate two parts to represent, Implementation process and New DANP algorithm. The executive process is divided by three steps as following (Fig.3):

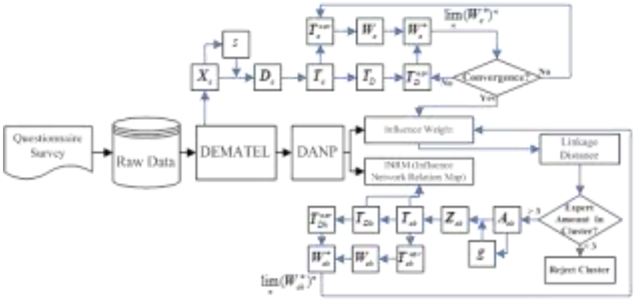


Fig. 3 New DANP Method Procedure (form authors)

Then, this part's will point out how to run New DANP algorithm so we illustrate detail steps under the following:

Step1. Structured each direct-influence matrix by scores.

An assessment of the relationship between each criterion is made according to the opinions of sophisticated experts through questionnaire's survey, using a scale ranging from 0 to 4, with scores represented by natural language: 'absolutely no influence' (0), 'low influence' (1), 'medium influence' (2), 'high influence' (3), and 'very high influence' (4). The sophisticated experts are required to indicate the direct influence by a pair-wise comparison, and if they believe that criterion *i* has an effect and influence on criterion *j*, they should indicate this by . Thus, the matrix $\boldsymbol{X}_c = [x_c^{ij}]_{n\times n}$ of direct relationships can be obtained as shown on Eq. (1). All diagonal of criteria are zero by pair-wise comparison.

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

Step2. Normalizing the direct-influence matrix

The normalized matrix D_c is acquired by using Eq. (2). The maximum total of rows or lines is one.

$$\boldsymbol{D}_c = \boldsymbol{X}_c / s \quad (2)$$

where, $s = \max_{i,j}\left\{\max_i \sum_{j=1}^{n} x_c^{ij}, \max_j \sum_{i=1}^{n} x_c^{ij}\right\}$, $i, j \in \{1, 2\cdots, n\}$

Step3. Attain a total-influential matrix of criteria and dimension

After normalized direct-influential matrix, the total-influential matrix $\boldsymbol{T}_c$ can be obtained from Eq. (3), in which $\boldsymbol{I}$ denotes the identity matrix.

$$\begin{aligned}\boldsymbol{T}_c &= \boldsymbol{D}_c + \boldsymbol{D}_c^2 + \cdots + \boldsymbol{D}_c^g \\ &= \boldsymbol{D}_c(\boldsymbol{I} + \boldsymbol{D}_c + \boldsymbol{D}_c^{\,2} + \ldots + \boldsymbol{D}_c^{g-1})(\boldsymbol{I} - \boldsymbol{D}_c)(\boldsymbol{I} - \boldsymbol{D}_c)^{-1} \\ &= \boldsymbol{D}_c(\boldsymbol{I} - \boldsymbol{D}_c^g)(\boldsymbol{I} - \boldsymbol{D}_c)^{-1} \\ &= \boldsymbol{D}_c(\boldsymbol{I} - \boldsymbol{D}_c)^{-1}, \text{ when } \lim_{g\to\infty} \boldsymbol{D}_c^g = [0]_{n\times n}\end{aligned} \tag{3}$$

where $\boldsymbol{D}_c = \left[D_c^{ij}\right]_{n\times n}$, $0 < D_c^{ij} < 1$, $0 < \sum_{j=1}^{n} D_c^{ij} \le 1$ and $0 < \sum_{i=1}^{n} D_c^{ij} \le 1$, and at least one rows or lines of the summation (but not all) equals one; then, $\lim_{g\to\infty} \boldsymbol{D}_c^g = [0]_{n\times n}$ can be guaranteed.

Two different total influence matrices are then applied. The total-influential matrix of criteria $\boldsymbol{T}_c = \left[t_{uv}^{ij}\right]_{n_i n_j}$ can be obtained as in Eq. (4), pertains to n criteria, while the second one, The total-influential matrix of dimension $\boldsymbol{T}_D = \left[t_D^{ij}\right]_{m\times m}$ can be attained by $t_D^{ij} = \frac{1}{n_i n_j}\sum_{u=1}^{n_i}\sum_{v=1}^{n_j} t_{uv}^{ij}$ as in Eq. (5), is devoted to m dimensions (clusters) from $\boldsymbol{T}_c$:

$$\boldsymbol{T}_c = \begin{array}{c} \\ D_1 \begin{smallmatrix} c_{11} \\ c_{12} \\ \vdots \\ c_{1n_1} \end{smallmatrix} \\ \vdots \\ D_i \begin{smallmatrix} c_{i1} \\ c_{i2} \\ \vdots \\ c_{in_i} \end{smallmatrix} \\ \vdots \\ D_m \begin{smallmatrix} c_{m1} \\ c_{m2} \\ \vdots \\ c_{mn_m} \end{smallmatrix} \end{array} \begin{array}{c} \begin{matrix} D_1 & \cdots & D_j & \cdots & D_m \\ c_{11}\ldots c_{1n_1} & \cdots & c_{j1}\ldots c_{jn_j} & \cdots & c_{m1}\ldots c_{mn_m} \end{matrix} \\ \begin{bmatrix} \boldsymbol{T}_c^{11} & \cdots & \boldsymbol{T}_c^{1j} & \cdots & \boldsymbol{T}_c^{1m} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{i1} & \cdots & \boldsymbol{T}_c^{ij} & \cdots & \boldsymbol{T}_c^{im} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{m1} & \cdots & \boldsymbol{T}_c^{mj} & \cdots & \boldsymbol{T}_c^{mm} \end{bmatrix} \end{array} \tag{4}$$

where $\boldsymbol{T}_c^{ij} = \left[t_{uv}^{ij}\right]_{n_i n_j}$ then $t_D^{ij} = \frac{1}{n_i n_j}\sum_{u=1}^{n_i}\sum_{v=1}^{n_j} t_{uv}^{ij}$.

$$\boldsymbol{T}_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1m} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{im} \\ \vdots & & \vdots & & \vdots \\ t_D^{m1} & \cdots & t_D^{mj} & \cdots & t_D^{mm} \end{bmatrix} \tag{5}$$

Step4. Find the normalized matrix by dimensions and clusters.

Normalize $\boldsymbol{T}_c$ with the total degrees of effect and influence of the dimensions and clusters to obtain $\boldsymbol{T}_c^{nor}$, as shown in Eq.(6).

$$\boldsymbol{T}_c^{nor} = \begin{array}{c} \\ D_1 \begin{smallmatrix} c_{11} \\ c_{12} \\ \vdots \\ c_{1n_1} \end{smallmatrix} \\ \vdots \\ D_i \begin{smallmatrix} c_{i1} \\ c_{i2} \\ \vdots \\ c_{in_i} \end{smallmatrix} \\ \vdots \\ D_m \begin{smallmatrix} c_{m1} \\ c_{m2} \\ \vdots \\ c_{mn_m} \end{smallmatrix} \end{array} \begin{array}{c} \begin{matrix} D_1 & \cdots & D_j & \cdots & D_m \\ c_{11}\ldots c_{1n_1} & \cdots & c_{j1}\ldots c_{jn_j} & \cdots & c_{m1}\ldots c_{mn_m} \end{matrix} \\ \begin{bmatrix} \boldsymbol{T}_c^{nor_{11}} & \cdots & \boldsymbol{T}_c^{nor_{1j}} & \cdots & \boldsymbol{T}_c^{nor_{1m}} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{nor_{i1}} & \cdots & \boldsymbol{T}_c^{nor_{ij}} & \cdots & \boldsymbol{T}_c^{nor_{im}} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{nor_{m1}} & \cdots & \boldsymbol{T}_c^{nor_{mj}} & \cdots & \boldsymbol{T}_c^{nor_{mm}} \end{bmatrix} \end{array} \tag{6}$$

where $\boldsymbol{T}_c^{nor_{ij}} = \left[t_{uv}^{ij} \Big/ \sum_{v=1}^{n_j} t_{uv}^{ij}\right]_{n_i n_j}$.

The total-influential matrix of dimension $\boldsymbol{T}_D$ also needs to be normalized by dividing it by the following formula: $t_D^i = \sum_{j=1}^{m} t_D^{ij}$

$$\boldsymbol{T}_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1m} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{im} \\ \vdots & & \vdots & & \vdots \\ t_D^{m1} & \cdots & t_D^{mj} & \cdots & t_D^{mm} \end{bmatrix} \begin{matrix} \to \sum_{j=1}^{m} t_D^{1j} = t_D^1 \\ \\ \to \sum_{j=1}^{m} t_D^{ij} = t_D^i \\ \\ \to \sum_{j=1}^{m} t_D^{mj} = t_D^m \end{matrix} \tag{7}$$

Therefore, the total-influential matrix can be normalized and presented as $\boldsymbol{T}_D^{nor}$. Then, the sum of each row can be defined as $t_D^i = \sum_{j=1}^{m} t_D^{ij}$, where $i = 1,\ldots,m$, and $\boldsymbol{T}_D$ can be normalized by the rows of sums by dividing the elements in each row by the sum of the row to obtain as in Eq. (7). Therefore, a total-influential matrix $\boldsymbol{T}_D$ can be normalized and represented as $\boldsymbol{T}_D^{nor}$. $\boldsymbol{T}_D^{nor} = \left[t_D^{ij} / t_D^i\right]_{m\times m}$, as in Eq. (8). Then, each row of the normalized $\boldsymbol{T}_D^{nor}$ can be summed to equal one, so that $\sum_{j=1}^{m} t_D^{nor_{ij}} = 1$.

$$\boldsymbol{T}_D^{nor} = \begin{bmatrix} t_D^{11}/t_D^1 & \cdots & t_D^{1j}/t_D^1 & \cdots & t_D^{1m}/t_D^1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_D^{i1}/t_D^i & \cdots & t_D^{ij}/t_D^i & \cdots & t_D^{im}/t_D^i \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_D^{m1}/t_D^m & \cdots & t_D^{mj}/t_D^m & \cdots & t_D^{mm}/t_D^m \end{bmatrix} = \begin{bmatrix} t_D^{nor_{11}} & \cdots & t_D^{nor_{1j}} & \cdots & t_D^{nor_{1m}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_D^{nor_{i1}} & \cdots & t_D^{nor_{ij}} & \cdots & t_D^{nor_{im}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_D^{nor_{m1}} & \cdots & t_D^{nor_{mj}} & \cdots & t_D^{nor_{mm}} \end{bmatrix} \tag{8}$$

Step5. Build an unweighted super-matrix

Then, the total-influential matrix is normalized into a super-matrix according to the interdependence between the relationships of the dimensions and clusters to obtain an unweighted super-matrix, $\boldsymbol{W}_c$, as shown in Eq. (9).

$$\boldsymbol{W}_c = \left(\boldsymbol{T}_c^{nor}\right)' = \begin{array}{c} \\ D_1 \begin{smallmatrix} c_{11} \\ \vdots \\ c_{1n_1} \end{smallmatrix} \\ \vdots \\ D_i \begin{smallmatrix} c_{i1} \\ \vdots \\ c_{in_i} \end{smallmatrix} \\ \vdots \\ D_m \begin{smallmatrix} c_{m1} \\ \vdots \\ c_{mn_m} \end{smallmatrix} \end{array} \begin{array}{c} \begin{matrix} D_1 & \cdots & D_j & \cdots & D_m \\ c_{11}\ldots c_{1n_1} & \cdots & c_{j1}\ldots c_{jn_j} & \cdots & c_{m1}\ldots c_{mn_m} \end{matrix} \\ \begin{bmatrix} \boldsymbol{W}_c^{11} & \cdots & \boldsymbol{W}_c^{i1} & \cdots & \boldsymbol{W}_c^{m1} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}_c^{1j} & \cdots & \boldsymbol{W}_c^{ij} & \cdots & \boldsymbol{W}_c^{mj} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}_c^{1m} & \cdots & \boldsymbol{W}_c^{im} & \cdots & \boldsymbol{W}_c^{mm} \end{bmatrix} \end{array} \tag{9}$$

Unweighted super-matrix $\boldsymbol{W}_c$ is the matrix transposed from $\boldsymbol{T}_c^{nor}$ in order to use a concept of analytic network process (basic concept from the ANP by Saaty (1996), but different from the traditional ANP). If a blank or 0 is shown in the matrix, this means that the dimensions and criteria are independent [8].

Step6. Build the weight super-matrix of the DANP method

The total-influential matrix $\boldsymbol{T}_c$ needs to be normalized by dividing the dimension and cluster as shown in Eq. (7), so $\boldsymbol{T}_c$ is normalized by summarizing the row by dimensions and clusters to obtain $\boldsymbol{T}_c^{nor}$. An unweighted super-matrix $\boldsymbol{W}_c$ can be obtained by transposing $\boldsymbol{T}_c^{nor}$, i.e., $\boldsymbol{W}_c = \left(\boldsymbol{T}_c^{nor}\right)'$. Using (Eq. (9)), a weighted super-matrix $\boldsymbol{W}_c^*$ (improving the traditional ANP by using equal weights to make it appropriate for the real world) can be obtained by the product of $(\boldsymbol{T}_D^{nor})'$ and $\boldsymbol{W}_c$, i.e., $\boldsymbol{W}_c^* = (\boldsymbol{T}_D^{nor})'\boldsymbol{W}_c$ (Eq. (10)). This result demonstrates that these influential level values are the basis of normalization to determine a weighted super-matrix.

$$W_c^* = (T_D^{nor})' W_c = \begin{bmatrix} t_D^{nor_{11}} W_c^{11} & \cdots & t_D^{nor_{i1}} W_c^{i1} & \cdots & t_D^{nor_{m1}} W_c^{m1} \\ \vdots & & \cdots & & \vdots \\ t_D^{nor_{1j}} W_c^{1j} & \cdots & t_D^{nor_{ij}} W_c^{ij} & \cdots & t_D^{nor_{mj}} W_c^{mj} \\ \vdots & & \vdots & & \vdots \\ t_D^{nor_{1m}} W_c^{1m} & \cdots & t_D^{nor_{im}} W_c^{im} & \cdots & t_D^{nor_{mm}} W_c^{mm} \end{bmatrix} \qquad (10)$$

Step 7: Obtain influence weight of the DANP method

Limit the weighted super-matrix by raising it to a sufficiently large power φ until it converges and becomes a long-term stable super-matrix to obtain global priority vector, which defines the influential weights $w = (w_1, \ldots, w_j, \ldots, w_n)$ from $\lim_{\varphi \to \infty} (W_c^*)^{\varphi}$ for the criteria.

Step 8: Separate each cluster with closer weight of criteria

In this step, we combine the cluster analysis method to divide clusters with closer weight of criteria. Cluster analysis is the task of grouping a set of objects in the way that objects in the same group (called cluster) are more similar to each other than to those in other clusters. Connectivity based clustering, also known as hierarchical clustering, is based on the core idea of objects being more related to nearby objects than to objects farther away. As such, these algorithms connect "objects" to form "clusters" based on their distance. A cluster can be described largely by the maximum distance needed to connect parts of the cluster. At different distances, different clusters will form, which can be represented using a "dendrogram", which explains where the common name "hierarchical clustering". And there are single linkage (minimize distance), complete linkage (maximize distance), average linkage (average above-mentioned method), and ward method (minimize distance for sum of square). This algorism adopts ward method to classify the cluster.

Step 9: Rerun step1-step7 with each cluster

Here, we used the average method to sum up each cluster. After that, we reran the process from step 1 and to step 7, with the some procedure above. And the total influenced-matrix and influence weight were gained.

Step 10: Analysis the result base on Total influence-matrix

At this stage, the row sums and the column sums of the matrix components are separately expressed as vector $r = \left[\sum_{j=1}^{n} t_c^{ij}\right] = (r_1, \ldots, r_i, \ldots, r_n)'$ and vector $s = \left[\sum_{i=1}^{n} t_c^{ij}\right]' = (s_1, \ldots, s_j, \ldots, s_n)'$ by using Eqs. (11)-(12). Let $i = j$ and $i, j \in \{1, 2, \ldots, n\}$; the horizontal axis vector $(r_i + s_i)$ is then defined by adding r_i to s_i, to illustrate the influence of the criterion and called "promince value". Similarly, the vertical axis vector $(r_i - s_i)$ is defined by subtracting r_i from s_i, which may divide the criteria into a causal cluster and an affected cluster (called "Relation value"). In general, when $(r_i - s_i)$ is positive, the criterion is part of the causal group; i.e., criterion affects other criteria. By contrast, if $(r_i - s_i)$ is negative, the criterion is part of the affected group; i.e., criterion i is influenced by other criteria. Therefore, a causal graph can be achieved by mapping the data set of ($r_i + s_i$, $r_i - s_i$), the so-called INRM, to provide a valuable approach to decide how the preferred values in each dimension and criterion can be improved based on the INRM,

$$T_c = [t_c^{ij}]_{n \times n},\ i, j \in \{1, 2, \ldots, n\}$$

$$r = \left[\sum_{j=1}^{n} t_c^{ij}\right]_{n \times 1} = \left[t_c^{i}\right]_{n \times 1} = (r_1, \ldots, r_i, \ldots, r_n)' \qquad (11)$$

$$s = \left[\sum_{i=1}^{n} t_c^{ij}\right]'_{1 \times n} = \left[t_c^{j}\right]_{n \times 1} = (s_1, \ldots, s_j, \ldots, s_n)' \qquad (12)$$

IV. Empirical case by appraisal system of B&B

We investigated 32 experts and 30 questionnaires were recovered. We separate total evaluation indexes to dimension and criteria. There are four dimensions; $\boldsymbol{D}_1$ Physical environment, $\boldsymbol{D}_2$ Room facilities, $\boldsymbol{D}_3$ Safety management, and $\boldsymbol{D}_4$ Service quality. There are three criteria in Physical environment's dimension; C_{11} Building outlook, C_{12} Landscape, and C_{13} Environment maintenance. The dimensions of Room facilities include C_{21} Neatness, C_{22} Brightness & freshness and C_{23} Privacy & comfort. And there are three criteria in Safety management; C_{31} Fire safety equipments, C_{32} Disaster prevention & rescue and C_{33} Crisis management. Finally, the dimensions of Service quality have three criteria; C_{41} Staff manners, C_{42} Meal serving and C_{43} Information service.

First, individual influence weights are obtained by running the DANP model. The influence weight means the expert perception for solving the problem. The value is larger that means the criterion is more important than another's. That is to say, each expert has unique perception in their mind. For example, first expert consider C_{21} is most important for improving B&B quality. Next, it's C_{13}, C_{22}, C_{32}, C_{33}, C_{12}, C_{11}, C_{23}, C_{31}, C_{41}, C_{42}, and C_{43}. The second expert has different perception. The expert feel C_{22} just most important criterion for solving problem. The sequence is C_{21}, C_{13}, C_{43}, C_{12}, C_{23}, C_{31}, C_{33}, C_{32}, C_{11}, C_{42}, and C_{41}. Therefore, we can easier observe that there is individual thinking in expert's mind (Table 3).

Table 3 the influence weight of individual expert perception

Expert Number	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
1	0.086	0.086	0.101	0.107	0.094	0.083	0.082	0.090	0.089	0.081	0.051	0.051
2	0.079	0.083	0.089	0.092	0.096	0.083	0.083	0.080	0.082	0.071	0.076	0.085
3	0.089	0.089	0.107	0.099	0.083	0.077	0.084	0.069	0.062	0.093	0.090	0.060
4	0.066	0.079	0.084	0.121	0.087	0.083	0.098	0.089	0.062	0.069	0.100	0.062
5	0.076	0.078	0.078	0.090	0.087	0.084	0.087	0.084	0.084	0.087	0.093	0.073
6	0.109	0.109	0.103	0.097	0.089	0.096	0.082	0.107	0.049	0.053	0.077	0.029
7	0.082	0.082	0.085	0.091	0.085	0.084	0.084	0.085	0.094	0.084	0.085	0.060
8	0.076	0.074	0.089	0.089	0.082	0.068	0.089	0.089	0.089	0.089	0.089	0.080
9	0.107	0.102	0.094	0.089	0.105	0.078	0.061	0.097	0.108	0.053	0.059	0.048
10	0.082	0.082	0.082	0.082	0.082	0.082	0.088	0.088	0.088	0.082	0.082	0.082
11	0.088	0.089	0.109	0.093	0.076	0.099	0.077	0.088	0.080	0.066	0.092	0.044
12	0.083	0.083	0.083	0.069	0.083	0.083	0.086	0.086	0.086	0.086	0.086	0.086
13	0.088	0.104	0.118	0.116	0.118	0.089	0.053	0.055	0.046	0.075	0.096	0.043
14	0.110	0.107	0.101	0.104	0.091	0.077	0.086	0.090	0.074	0.057	0.052	0.052
15	0.115	0.116	0.113	0.105	0.099	0.054	0.065	0.084	0.076	0.066	0.060	0.048
16	0.065	0.100	0.096	0.094	0.090	0.071	0.083	0.081	0.078	0.103	0.073	0.066
17	0.082	0.087	0.109	0.110	0.110	0.068	0.077	0.080	0.075	0.071	0.072	0.060
18	0.153	0.104	0.151	0.125	0.082	0.058	0.089	0.074	0.020	0.036	0.066	0.041
19	0.098	0.097	0.076	0.086	0.086	0.080	0.070	0.091	0.070	0.076	0.091	0.080

Expert Number	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
20	0.072	0.087	0.095	0.090	0.087	0.060	0.082	0.093	0.081	0.083	0.097	0.075
21	0.069	0.061	0.069	0.086	0.093	0.082	0.080	0.096	0.090	0.092	0.095	0.088
22	0.092	0.105	0.096	0.092	0.069	0.083	0.078	0.090	0.078	0.079	0.072	0.068
23	0.105	0.105	0.114	0.094	0.099	0.066	0.080	0.080	0.084	0.060	0.064	0.050
24	0.065	0.072	0.100	0.110	0.089	0.066	0.035	0.059	0.050	0.127	0.135	0.093
25	0.112	0.103	0.125	0.135	0.113	0.091	0.032	0.082	0.042	0.072	0.082	0.012
26	0.085	0.085	0.087	0.087	0.072	0.068	0.081	0.096	0.095	0.083	0.087	0.074
27	0.080	0.073	0.089	0.077	0.090	0.068	0.079	0.107	0.103	0.074	0.108	0.053
28	0.046	0.056	0.105	0.107	0.085	0.064	0.073	0.064	0.062	0.128	0.113	0.098
29	0.093	0.093	0.104	0.088	0.084	0.083	0.075	0.082	0.072	0.092	0.084	0.052
30	0.077	0.086	0.082	0.096	0.082	0.076	0.078	0.088	0.081	0.079	0.100	0.076

This study uses the ward method to divide each cluster and obtain rescaled distance. The result of hierarchical cluster analysis is obviously represented by dendrogram (as shown Fig. 4). It can separate two clustering as rescaled distance as 13. The first cluster set is (10, 12, 2, 8, 26, 20, 5, 30, 7, 21, 27, 3, 29, 16, 19, 22, 11, 4, 24, and 28). Second cluster set is (1, 17, 15, 23, 14, 9, 6, 13, 25, and 18).

Then, when rescaled distance is 10, the clustering is divided into three. The first cluster set is (10, 12, 2, 8, 26, 20, 5, 30, 7, 21, 27, 3, 29, 16, 19, 22, 11, and 4). Second cluster set is (24 and 28). Third cluster set is (1, 17, 15, 23, 14, 9, 6, 13, 25, and 18). Then, the first batches of outlier are number 24 and 28.

After that, the clustering is divided into four when rescaled distance as 6. The first cluster set is (10, 12, 2, 8, 26, 20, 5, 30, 7, 21, 27, 3, 29, 16, 19, 22, 11, and 4). Second cluster set is (24 and 28). Third cluster's set is (1, 17, 15, 23, 14, 9, and 6). Fourth cluster set is (13, 25, and 18). Then, the second batches of outlier are number 13, 25 and 28.

At the end, it can separate 6 clusters when rescaled distance is 4. The first cluster set is (10, 12, 2, 8, 26, 20, 5, 30, 7, 21, and 27). Second cluster set is (3, 29, 16, 19, 22, 11, and 4). Third cluster set is (24 and 28). Fourth cluster set is (1, 17, 15, 23, 14, 9, and 6). Fifth cluster set is (13, and 25). Sixth cluster set is (18). The third batches of outlier are number 13, 25 and 28.

As we can see, the last batch of outlier is no change. So, we can stop rescaling when analyst has found the batches of outlier number are the same. Finally, we discover that number 24, 28, 13, 25, and 28 outliers are very sensitive which can disorder the whole system. Thus, we just use (10, 12, 2, 8, 26, 20, 5, 30, 7, 21, and 27), (3, 29, 16, 19, 22, 11, and 4) and (1, 17, 15, 23, 14, 9, and 6) these three clusters, to run the system.

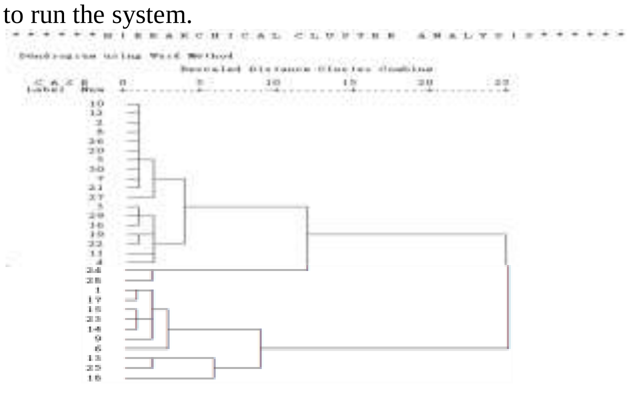


Fig. 4 Dendrogram of B&B 30 experts

V. Conclusion and Suggestion

The hybrid model can output some visual maps to summarize those complex human thinking by its systematization method, and provide some vital information to decision maker, which made this model very suitable for practical issues. Therefore this method has been used in a wide range of social sciences areas [2, 3, 5, 6]. This D-DANP model uses questionnaire to collect raw data from expert. Therefore, the most important thing is to collect effective and reliable sample by confirming the quality of the expert. However, the D-DANP can not provide the more reliable INRM without finding the outlier form raw data and take an example for showing the dismiss problem. Then, this paper describe how to work the modified D-DANP model that our proposed and develops trustworthy INRM by eliminating outlier which can be found by cluster analysis technique according to influential weight result. Finally, we discover that number 24, 28, 13, 25, and 28 experts are very sensitive which can disorder the whole system in the empirical case of appraisal system of B&B. Thus, we just use other samples to run the system to achieve this paper's purpose.

The future studies can be divided into two ways. The first one is modifying our model, because there is more than one approach to solve the outlier problem, which the future study can combine with other methods to develop a more concise manner. And the second improving is applying to practical issues, since D-DANP model had been proposed to solve those "selecting" and "evaluation" issues. The following scholars can combine with VIKOR performance evaluation to extend our model to resolve "devising" problem.

This mode is only providing another solution for the trustworthy of raw data, and it can be used to the original D-DANP issue. So, the following studies may combine with MDDANP and VIKOR, to develop sophisticated strategy for improvement.

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