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# Combining fuzzy AHP with MDS in identifying the preference similarity of alternatives

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**Abstract**

Multidimensional scaling (MDS) analysis is a dimension-reduction technique that is used to estimate the coordinates of a set of objects. However, not every criterion used in multidimensional scaling is equally and precisely weighted in the real world. To address this issue, we use fuzzy analytic hierarchy process (FAHP) to determine the weighting of subjective/perceptive judgments for each criterion and to derive fuzzy synthetic utility values of alternatives in a fuzzy multi-criteria decision-making (FMCDM) environment. Furthermore, we combine FAHP with MDS to identify the similarities and preferences of alternatives in terms of the axes of the space, which represent the perceived attributes and characteristics of those alternatives. By doing so, the visual dimensionality and configuration or pattern of alternatives whose weighted distance structure best fits the input data can be obtained and explained easily. A real case of expatriate assignment decision-making was used to demonstrate that the combination of FAHP and MDS results in a meaningful visual map.


*Keywords:* Multidimensional scaling (MDS); Fuzzy analytic hierarchy process (FAHP); Fuzzy multi-criteria decision-making (FMCDM); Expatriate assignment

## 1. Introduction

Multidimensional scaling (MDS) analysis is used to provide a visual representation of a complex set of relationships (or the pattern of proximities among a set of objects) that can be scanned at a glance. In general, the purpose of an MDS analysis is to detect meaningful underlying dimensions that allow the researcher to explain observed similarities or dissimilarities (distances) between the investigated objects. According to a measure of similarity or distance based on subjects' direct assessment that has been computed for all pairs of objects, a map or configuration with located objects is developed. However, not each criterion utilized in developing a multidimensional scaling configuration is equally and precisely weighted in the real world.

Developed by Saaty [12], the analytic hierarchy process (AHP) is a decision analysis method that considers both qualitative and quantitative information and combines them by decomposing ill-structured problems into systematic hierarchies to rank alternatives based on a number of criteria. AHP possesses a number of benefits over other multi-attribute decision methods. First, AHP provides a proven, effective means of dealing with complex decision-making and expediting the decision-making process. Second, AHP provides a useful mechanism for checking the consistency of the evaluation measures, which enables the decision-maker to incorporate subjectivity, experience, and knowledge into the decision process in an intuitive and natural way. Finally, AHP computes the weight for each criterion and the final weighted average score for each alternative. This information gives us insights into the elements of the process, thereby giving the analyst a better understanding of the final decision.

When people encounter uncertain or vague decision-making problems in the real world, they often express their thinking and subjective perception in words instead of probability and statistics. But the problem with words is that their meanings are often vague. Furthermore, even when people use the same words, individual judgment of events is invariably subjective and may differ. Moreover, even if the meaning of a word is well defined (e.g., the linguistic comparison labels in the standard

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AHP questionnaire responses), when we use the word to define a set, the boundary that separates whether an object does or does not belong to the set is often fuzzy or vague. This is why fuzzy numbers and fuzzy sets have been introduced to characterize linguistic variables. The preferences in AHP are essentially human judgments based on one's perception (this is especially true for intangibles), and we believe the fuzzy approach allows for a more accurate description of the decision making process [8,9].

The primary focus of this article is to combine fuzzy analytic hierarchy process (FAHP) with MDS to identify the similarities and preferences of alternatives in terms of the axes of the space, which represent perceived attributes and characterize those alternatives. By doing so, the visual dimensionality and configuration or pattern of alternatives whose weighted distance structure best fits the input data can be obtained and explained easily. In sum, FAHP plus MDS provides three advantages for decision-makers: (1) a clear snapshot of alternatives could be easily obtained; (2) the reduced dimensions, after clearly explained and labeled, could be treated as a mental shortcut for decision-makers in the future; (3) distinct alternatives clusters could be obtained easily based on the measure of psychological distances.

The remainder of this paper is organized as follows. The notion of fuzzy weights and synthetic utility values for AHP are introduced in Section 2. The method of combining FAHP with MDS for identifying the fuzzy preference similarity of alternatives in terms of a meaningful visual map is proposed in Section 3. We use a real case of expatriate assignment decision-making to demonstrate that the combined method results in a satisfactory and effective visual map in Section 4. Our conclusions are presented in the last section.

## 2. Fuzzy weights and synthetic utility values for analytic hierarchy process

Since analytic hierarchy process (AHP) was introduced by Saaty [11,12] it has become a popular technique that has been employed to model subjective decision-making processes based on multiple criteria. However, the importance of each criterion is not necessarily equal. To resolve this problem, Saaty [12] uses the eigenvector method to determine the relative importance (weights) among the various criteria based on the pairwise comparison matrix in AHP.

If $\boldsymbol{A} = [a_{ij}]$ is a positive reciprocal matrix, then the geometric mean of each row $r_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}$. Saaty [12] defined $\lambda_{\max}$ as the largest eigenvalue of $\boldsymbol{A}$, and the weights $w_i$ as the components of the normalized eigenvector corresponding to $\lambda_{\max}$, where $w_i = r_i/(r_1 + r_2 + \cdots + r_n)$.

In crisp AHP, Saaty [12] warned against the difficulties of having inconsistent comparisons in the analysis. The decision maker has to redo the ratios when the comparison matrix fails to pass the consistency test, because the lack of consistency in decision making can lead to inconsistent results. So in order to avoid using inadequate assessments data when a person provides his or her opinions inconsistently, we must calculate a consistency index to ensure that AHP's pairwise comparison method is consistent. The consistency index is calculated as follows [12]:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{1}$$

where $\lambda_{\max}$ denotes the maximal eigenvalue of the matrix $\boldsymbol{R}$. When matrix $\boldsymbol{R}$ is consistent then $\lambda_{\max} = n$ and $CI = 0$. Consistency ratio ($=CI/RI(n)$) is the ratio of the consistency index to the corresponding random index (i.e., the average consistency index of 100 randomly generated (inconsistent) pairwise comparisons matrices). In Saaty's opinion, a consistency ratio ($CR$) of 0.1 or less is acceptable under the condition that all judgment matrices given by evaluators for the same problem of decision-making are of acceptable consistency. If $CR$ is not acceptable, judgements should be revised. Otherwise the decision will not be adequate.

Fuzzy set theory was originally introduced by Zadeh [14], and after Bellman and Zadeh [2] subsequently described the decision-making methods in fuzzy environments, an increasing number of studies investigated uncertain fuzzy problems by applying fuzzy set theory (e.g. [6,13]). Here, for each criterion specified, an evaluator must give it a weight. But since an evaluator's judgment is inherently subjective, these weights are also inexact and imprecise. This is why fuzzy numbers are used to represent this type of fuzzy data [7]. According to Zadeh [15], it is very difficult for conventional quantification methods such as a scale from 1 to 10 to express reasonably those situations that are overtly complex or hard to define. This is why a linguistic variable is necessary in these situations. A linguistic variable is a variable whose values are not numbers but words or sentences from a natural or artificial language. Linguistic variables are used to represent the imprecise nature of human cognition when we try to translate people's opinions into spatial data [15]. Here, we use linguistic variables to compare two evaluation criteria in a fuzzy environment. For the ''importance'' criterion, we use the following five basic linguistic terms to express the degree of importance: ''absolutely important,'' ''very strongly important,'' ''essentially important,'' ''weakly important,'' and ''equally important.'' For the ''performance'' alternative, we use the five basic terms below to express satisfaction: ''very dissatisfied'', ''dissatisfied'', ''fair'', ''satisfied'', and ''very satisfied.'' Triangular fuzzy numbers (TFN) are then used to compare evaluation criteria and alternatives. Using the characteristics of TFN and the extension principle put forward by Zadeh [15], the operations on two triangular fuzzy numbers are easy to do.

Here, we employ Buckley's [4] method of geometric mean to fuzzify a hierarchical analysis by allowing fuzzy numbers for pairwise comparisons and finding fuzzy weights for each criterion and fuzzy performance for the alternatives in each criterion. Barzilai [1] has verified that the geometric mean is the only method for deriving weights from multiplicative pairwise comparisons, since it satisfies fundamental consistency requirements.

A fuzzy positive reciprocal matrix $\tilde{\boldsymbol{A}} = [\tilde{a}_{ij}]$ is used to extend the technique of using geometric mean to define $\tilde{r}_i$, the fuzzy geometric mean of each row, and $\tilde{w}_i$, the fuzzy weight, with respect to each criterion as follows [4]:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots \otimes \tilde{a}_{in})^{1/n}; \qquad \tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n)^{-1} \tag{2}$$

Evaluators can define their own individual range for the linguistic variables employed based on their subjective judgments within a fuzzy scale in order to determine the performance value of each alternative. Let $\tilde{h}_{ai}^{k}$ represent the fuzzy performance score by the $k$-th evaluator of the $a$-th alternative under the $i$-th criterion. Since the perception of each evaluator varies according to individual experience and knowledge, and the definitions of linguistic variables also vary, we employ fuzzy geometric mean to integrate the fuzzy performance score $\tilde{h}_{ai}$ for $m$ evaluators. That is:

$$\tilde{h}_{ai} = (\tilde{h}_{ai}^{1} \otimes \tilde{h}_{ai}^{2} \otimes \ldots \tilde{h}_{ai}^{m})^{1/m} \tag{3}$$

Since a fuzzy number represents the fuzzy synthetic decision reached for each alternative, we need to defuzzify these fuzzy numbers in order to compare the alternatives in a non-fuzzy ranking method. In previous works, the procedure of defuzzification has been to locate the best non-fuzzy performance (BNP) value. In general, there are three methods to determine the BNP value: mean of maximal (MOM), center of area (COA), and $\alpha$-cut [10,16]. The center of area (COA) method is a simple and practical method, and there is no need to introduce the preferences of any evaluators. The COA method's BNP value for triangular fuzzy performance score $\tilde{h}_{ai} = (lh_{ai}, mh_{ai}, uh_{ai})$ can be calculated as follows:

$$\text{BNP}: \; x_{ai} = lh_{ai} + \frac{(uh_{ai} - lh_{ai}) + (mh_{ai} - lh_{ai})}{3}, \quad \forall a \tag{4}$$

## 3. Combining FAHP with MDS

For adequate analysis, we often reduce the dimensionality of the dataset in order to achieve a balance between parsimony of understanding and retention of sufficient information. Multi-dimensional scaling (MDS) is a technique for measuring the distances among psychological stimulus, which are represented as points in geometric space. We focus on the measurement of psychological distance, because evaluators often face subjective/perceptive judgments instead of physical phenomena such as distance (km) or temperature (degrees Celsius). The objective of MDS is to find the dimensionality and the pattern of points (alternatives) whose distance structure best fits the input data. For MDS, the axes of this space represent the perceived attributes/criteria that characterize those psychological stimuli. In other words, MDS uses similarities between pairs of stimuli to find a psychological distance between those stimuli. If one pair of stimuli is deemed more similar than another pair, the psychological distance between the first pair would be shorter than that between the second pair.

As we have mentioned earlier, the fuzzy synthetic utility values of alternatives are weighted by the importance priority of decision-making criteria. The Euclidean distance matrix of the alternatives, computed based on the above evaluation criteria, will serve as the input of MDS. But before doing this, we must first calculate the defuzzified synthetic performance values of the criteria based on Eq. (4) because the inputs to the MDS obtained from FAHP should not be fuzzy values. We then compute the distance matrix (reflecting the pairwise perceived preference in similarity) of the alternatives as the MDS input. For $n$-dimensions, the Euclidean distance function can be expressed as follows:

$$d_{ab} = \sqrt{\sum_{i=1}^{n} (x_{ai} - x_{bi})^2} \tag{5}$$

where $x_{ai}$ denotes the coordinate of alternative $a$ in dimension $i$; where $x_{bi}$ denotes the coordinate of alternative $b$ in dimension $i$.

In practice, a set of data is usually scaled in a varying number of dimensions ranging from one to four [3]. A statistic, called *stress*, is used to measure the goodness of fit. The correct number of dimensions is found by identifying the smallest possible number of dimensions that still has satisfactory stress levels. A solution with fewer dimensions is desirable if its stress value is less than 0.10.

The next step is to interpret and label the dimensions. Although the configuration resulting from MDS represents an approximation of the positioning of alternatives in the original multidimensional space, MDS has no built-in procedure for labeling the dimensions obtained. Researchers need to observe the linear or non-linear relationships between the dimensions and the original variables to help label the dimensions. We could further reduce the dimensions involved by using principal components analysis to help us interpret and label the dimensions we obtain from MDS. A basic purpose of principal components is to account for the total variation among the subjects in $p$-dimension space ($p < n$) by forming a new set of orthogonal and uncorrelated composite variates. And each member of the new set of variates is a linear combination of the original set of measurements.

## 4. Empirical study: a real case of expatriate assignment decision-making

### 4.1. Description of a FMCDM problem

Finding the right people for expatriate assignments and helping them stay there for the duration of their assignments within a globalized organization is a challenging task for international human resources management. Multinational companies need to understand a candidate's preferences, as well as a candidate's perception of the similarity and difference between the home country and the host country, so as to enhance the expatriates' satisfaction and develop appropriate international staffing strategies. After reviewing the related literature and consultation within our research group, we list here the following six distinct characteristics that influence successful expatriate assignments: (1) personal factors; (2) competence; (3) job characteristics; (4) family factors; (5) environmental factors; (6) organization relocation support [5]. We then consider three criteria in employee personal factors, three criteria in employee competence, five criteria in job characteristics, five criteria in family factors, four criteria in environmental factors, and five criteria in organization relocation support. We build a hierarchical framework to describe the above 6 characteristics and 25 criteria for an expatriate assignment evaluation (see Fig. 1).

The Tatung Company, with its headquarter in Taiwan, provides manufacturing services globally in computer displays, information appliances, home appliances, power, and energy. Here, we use Tatung as an example for understanding expatriates' perceptions of competing host countries by combining FAHP with MDS. We show that fuzzy MCDM provides a good evaluation method and appears to be more appropriate in the context of subjective judgment and limited rationality.

### 4.2. Results and discussions

We select 24 participants who already have expatriate experience or have potential opportunities to take expatriate assignments for the study. After checking the consistency of judgments in the pairwise comparison in AHP (i.e. the consistency index of judgment matrices is less than 0.1), we integrate their subjective judgments to develop the fuzzy criteria weights by fuzzy AHP with respect to characteristics using the fuzzy geometric mean as shown in Eq. (2). The selection of the host countries to receive expatriates is based on the scope of Tatung's global operation. Ten alternative host countries include the US, UK, Japan, China, Mexico, Europe, Canada, Singapore, South Korea, and Thailand. We then derive the final fuzzy weights and non-fuzzy BNP values corresponding to each criterion, as shown in Table 1.

The fuzzy performance scores of the host countries with respect to the criteria and the BNP values are shown in Table 2. Based on the overall synthetic performance values (based on the 25 criteria) of the host countries (see the bottom line of the table), the most preferred destination by the 24 participants is China, followed by US, Japan, Singapore, UK, Europe, Canada, South Korea, Thailand, and Mexico. Further investigation shows that there are three distinct clusters. Cluster 1 includes China, US, Japan, and Singapore, with synthetic performance values ranging from 73.376 to 74.278. Cluster 2 includes UK, Europe, and Canada, with synthetic performance values ranging from 67.629 to 69.360. Cluster 3 includes South

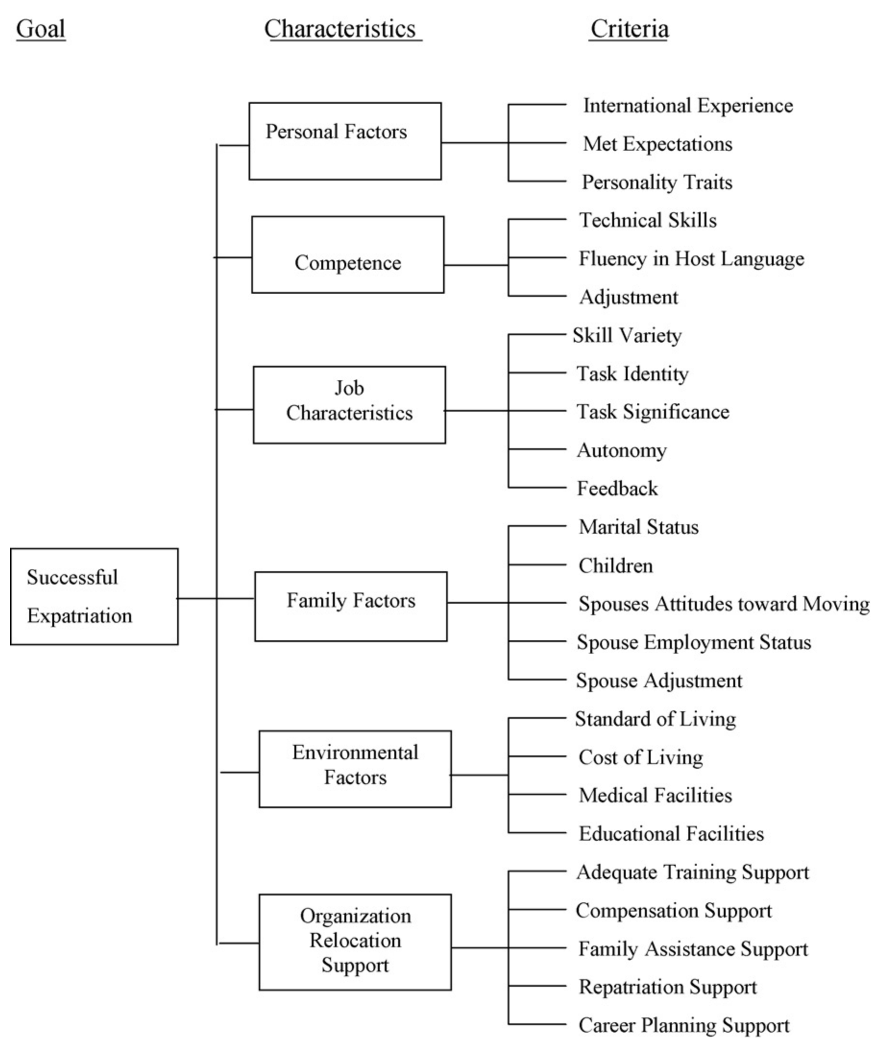


Fig. 1. Fuzzy MCDM hierarchical framework for expatriate assignment evaluation criteria.

Table 1
Criteria weights and factors for evaluating expatriate assignment's decision-making alternatives

| Characteristic/criterion | Weight | Total weights ($w_i$) |
|---|---|---|
| **Personal factor** | 0.241 (0.164, 0.232, 0.327) | |
| International experience | 0.406 (0.289, 0.392, 0.537) | 0.105 (0.048, 0.091, 0.176) [1] |
| Met expectation | 0.345 (0.229, 0.330, 0.475) | 0.090 (0.038, 0.077, 0.155) [2] |
| Personality | 0.285 (0.202, 0.278, 0.376) | 0.074 (0.033, 0.065, 0.123) [5] |
| **Competence** | 0.197 (0.130, 0.188, 0.274) | |
| Technical skills | 0.366 (0.261, 0.355, 0.483) | 0.078 (0.034, 0.067, 0.132) [3] |
| Fluency in host language | 0.346 (0.235, 0.333, 0.471) | 0.074 (0.030, 0.063, 0.129) [4] |
| Adjustment | 0.322 (0.229, 0.312, 0.424) | 0.068 (0.030, 0.059, 0.116) [6] |
| **Job characteristics** | 0.201 (0.137, 0.192, 0.273) | |
| Skill variety | 0.305 (0.211, 0.293, 0.411) | 0.066 (0.029, 0.056, 0.112) [7] |
| Task identity | 0.238 (0.158, 0.230, 0.327) | 0.052 (0.022, 0.044, 0.089) [8] |
| Task significance | 0.200 (0.134, 0.192, 0.274) | 0.043 (0.018, 0.037, 0.075) [12] |
| Autonomy | 0.168 (0.112, 0.160, 0.233) | 0.037 (0.015, 0.031, 0.064) [14] |
| Feedback | 0.130 (0.089, 0.126, 0.174) | 0.028 (0.012, 0.024, 0.047) [20] |
| **Family factor** | 0.141 (0.096, 0.136, 0.191) | |
| Marital status | 0.171 (0.116, 0.161, 0.235) | 0.026 (0.011, 0.022, 0.045) [22] |
| Children | 0.125 (0.083, 0.117, 0.173) | 0.019 (0.008, 0.016, 0.033) [25] |
| Spouse attitudes toward moving | 0.198 (0.136, 0.190, 0.267) | 0.030 (0.013, 0.026, 0.051) [18] |
| Spouse employment status | 0.318 (0.210, 0.308, 0.437) | 0.048 (0.020, 0.042, 0.083) [9] |
| Spouse adjustment | 0.231 (0.155, 0.224, 0.313) | 0.035 (0.015, 0.031, 0.060) [16] |
| **Environmental factor** | 0.145 (0.095, 0.139, 0.202) | |
| Standard of living | 0.239 (0.166, 0.226, 0.325) | 0.038 (0.016, 0.031, 0.066) [13] |
| Cost of living | 0.286 (0.200, 0.279, 0.379) | 0.045 (0.019, 0.039, 0.076) [10] |
| Medical facilities | 0.232 (0.164, 0.222, 0.310) | 0.036 (0.016, 0.031, 0.062) [15] |
| Educational facilities | 0.279 (0.191, 0.274, 0.373) | 0.044 (0.018, 0.038, 0.075) [11] |
| **Organizational relocation support** | 0.117 (0.080, 0.113, 0.159) | |
| Adequate training support | 0.190 (0.129, 0.180, 0.261) | 0.024 (0.010, 0.020, 0.042) [23] |
| Compensation support | 0.168 (0.111, 0.159, 0.234) | 0.021 (0.009, 0.018, 0.037) [24] |
| Family assistance support | 0.208 (0.135, 0.198, 0.291) | 0.026 (0.011, 0.022, 0.046) [21] |
| Repatriation support | 0.256 (0.168, 0.246, 0.354) | 0.032 (0.013, 0.028, 0.056) [17] |
| Career planning support | 0.224 (0.150, 0.217, 0.304) | 0.028 (0.012, 0.024, 0.048) [19] |

*Note*: The entries denote the defuzzified weights by using BNP, the values in the parentheses denote the fuzzy numbers, and the values in the square brackets denote the order of importance weights for the criteria.

Korea, Thailand, and Mexico, with synthetic performance values ranging from 60.106 to 62.326. The results are similar to our earlier findings by ranking the grade of grey relation based on TOPSIS concepts [5]. To discover the differences among countries within a cluster, we need to further analyze the evaluation results.

Moreover, we use MDS to obtain an overall visual positioning of the ten host countries based on the perceived expatriate assignment decision-making criteria. There are 25 original criteria, which are difficult to reduce down to 2 or 3 dimensions. Since the 25 criteria have been classified into 6 characteristics within the hierarchical framework (see Fig. 1), the 6 characteristics will be used instead of the original 25 criteria to help reduce the dimensionality of our problem. We first calculate the defuzzified synthetic performance values for the six characteristics based on the perceived preference data of the ten competing host countries. For example, we add the scores for international experience (4.528), met expectation (5.768), and personality (5.009) to get the perceived value for the characteristic of personal factor for China (15.305) (see Table 3). Next, the Euclidean distance matrix (reflecting the pairwise perceived preference similarity) of the ten host countries, computed based on the above six characteristics, will serve as the data input of MDS (see Table 4). For example, the Euclidean distance between China and Japan based on the above six aspects is obtained as follows from Eq. (5):

$$3.582 = [(15.305 - 15.298)^2 + (16.840 - 13.654)^2 + (15.637 - 15.834)^2 + (9.520 - 9.519)^2 + (8.654 - 10.162)^2 + (8.412 - 9.018)^2]^{1/2}$$

MDS results reveal a stress of 0.0238 in two dimensions, which is within the acceptable level. The two-dimensional coordinates of the ten countries are shown in Table 5 and the graphical solution is depicted in Fig. 2. In order to interpret and label the dimensions, a principal components factor analysis with varimax rotation was conducted for the six characteristics. Two common factors were extracted with a 93.42% cumulative proportion of total variance explained. The results are shown in Table 6. On one hand, factor 1 represents personal factors, competence, job characteristics, and family factors; factor 1 is labeled ‘‘perceived fit of expatriation’’. On the other hand, factor 2 represents the remaining two factors, which are environmental factors and organization relocation support; factor 2 is labeled ‘‘attractiveness of host country’’. The positioning of the ten countries in the factor space (shown in Fig. 3) corresponds with the positioning shown in Fig. 2. After

Table 2
Evaluation results for host countries based on the expatriate criteria

| Criterion | China | Japan | Thailand | The US | Mexico | The UK | Europe | Canada | Singapore | Korea |
|---|---|---|---|---|---|---|---|---|---|---|
| Personal factors | | | | | | | | | | |
| International experience | 4.528 (1) | 4.032 (3) | 3.304 (5) | 4.262 (2) | 2.980 (9) | 3.169 (8) | 3.189 (7) | 2.938 (10) | 3.519 (4) | 3.227 (6) |
| Met expectation | 5.768 (4) | 6.215 (1) | 3.532 (10) | 5.787 (3) | 4.209 (8) | 5.672 (5) | 5.459 (6) | 5.259 (7) | 5.877 (2) | 4.094 (9) |
| Personality | 5.009 (2) | 5.051 (1) | 3.760 (8) | 4.857 (3) | 3.316 (10) | 4.434 (5) | 4.236 (7) | 4.409 (6) | 4.840 (4) | 3.594 (9) |
| Competence | | | | | | | | | | |
| Technical skills | 5.542 (1) | 5.340 (3) | 4.063 (10) | 4.776 (4) | 4.066 (9) | 4.632 (5) | 4.244 (8) | 4.366 (7) | 5.387 (2) | 4.393 (6) |
| Fluency in host language | 6.136 (1) | 3.451 (7) | 3.347 (8) | 4.802 (3) | 2.903 (9) | 4.504 (4) | 3.464 (6) | 4.418 (5) | 5.325 (2) | 2.276 (10) |
| Adjustment | 5.162 (1) | 4.863 (2) | 4.354 (7) | 4.551 (4) | 3.837 (10) | 4.477 (5) | 4.334 (8) | 4.436 (6) | 4.821 (3) | 4.172 (9) |
| Job characteristics | | | | | | | | | | |
| Skill variety | 4.531 (2) | 4.671 (1) | 3.908 (8) | 4.482 (3) | 3.854 (10) | 4.096 (5) | 4.077 (7) | 3.860 (9) | 4.394 (4) | 4.087 (6) |
| Task identity | 3.425 (4) | 3.687 (1) | 2.811 (10) | 3.668 (2) | 3.124 (9) | 3.387 (6) | 3.439 (3) | 3.183 (7) | 3.416 (5) | 3.155 (8) |
| Task significance | 3.152 (2) | 3.080 (3) | 2.585 (10) | 3.288 (1) | 2.788 (8) | 2.868 (5) | 2.860 (6) | 2.810 (7) | 2.879 (4) | 2.697 (9) |
| Autonomy | 2.627 (1) | 2.464 (4) | 2.411 (6) | 2.568 (3) | 2.275 (10) | 2.410 (7) | 2.443 (5) | 2.368 (8) | 2.573 (2) | 2.316 (9) |
| Feedback | 1.903 (3) | 1.931 (2) | 1.680 (10) | 1.960 (1) | 1.696 (9) | 1.872 (4) | 1.853 (5) | 1.746 (7) | 1.821 (6) | 1.728 (8) |
| Family factors | | | | | | | | | | |
| Marital status | 1.466 (1) | 1.407 (2) | 1.242 (8) | 1.338 (4) | 1.220 (9) | 1.294 (7) | 1.315 (5) | 1.295 (6) | 1.368 (3) | 1.215 (10) |
| Children | 0.550 (8) | 0.616 (3) | 0.529 (10) | 0.580 (7) | 0.537 (9) | 0.591 (4) | 0.591 (4) | 0.591 (4) | 0.644 (1) | 0.616 (2) |
| Spouse attitude toward moving | 2.185 (2) | 2.234 (1) | 1.859 (9) | 2.140 (3) | 1.749 (10) | 1.906 (7) | 1.933 (6) | 1.957 (5) | 2.100 (4) | 1.883 (8) |
| Spouse employment status | 2.751 (8) | 2.841 (2) | 2.841 (2) | 2.905 (1) | 2.841 (2) | 2.751 (8) | 2.751 (8) | 2.841 (2) | 2.811 (6) | 2.811 (6) |
| Spouse adjustment | 2.568 (1) | 2.421 (3) | 2.321 (9) | 2.376 (4) | 2.304 (10) | 2.330 (7) | 2.330 (7) | 2.374 (5) | 2.438 (2) | 2.334 (6) |
| Environmental factors | | | | | | | | | | |
| Standard of living | 1.990 (9) | 3.217 (1) | 1.865 (10) | 3.143 (2) | 2.026 (8) | 3.071 (4) | 3.088 (3) | 2.927 (6) | 2.949 (5) | 2.273 (7) |
| Cost of living | 2.595 (1) | 0.694 (10) | 2.408 (2) | 0.982 (8) | 2.009 (3) | 0.942 (9) | 0.990 (7) | 1.162 (6) | 1.534 (5) | 1.697 (4) |
| Medical facilities | 1.609 (10) | 2.957 (1) | 1.786 (9) | 2.939 (4) | 2.156 (8) | 2.956 (2) | 2.940 (3) | 2.877 (6) | 2.877 (5) | 2.615 (7) |
| Educational facilities | 2.371 (8) | 3.295 (3) | 2.048 (10) | 3.408 (1) | 2.365 (9) | 3.214 (5) | 3.387 (2) | 3.234 (4) | 3.212 (6) | 2.777 (7) |
| Organization relocation support | | | | | | | | | | |
| Adequate training support | 1.596 (5) | 1.677 (1) | 1.361 (10) | 1.623 (3) | 1.417 (9) | 1.614 (4) | 1.639 (2) | 1.591 (6) | 1.578 (7) | 1.494 (8) |
| Compensation support | 1.386 (2) | 1.443 (1) | 1.317 (7) | 1.323 (5) | 1.315 (8) | 1.334 (4) | 1.319 (6) | 1.303 (9) | 1.341 (3) | 1.303 (10) |
| Family assistance support | 1.678 (3) | 1.708 (1) | 1.480 (10) | 1.653 (5) | 1.558 (9) | 1.643 (6) | 1.667 (4) | 1.643 (6) | 1.704 (2) | 1.630 (8) |
| Repatriation support | 2.025 (8) | 2.237 (3) | 1.880 (10) | 2.280 (1) | 1.998 (9) | 2.250 (2) | 2.211 (4) | 2.173 (5) | 2.155 (6) | 2.149 (7) |
| Career planning support | 1.727 (8) | 1.954 (2) | 1.704 (9) | 1.956 (1) | 1.561 (10) | 1.942 (3) | 1.917 (4) | 1.866 (5) | 1.814 (6) | 1.791 (7) |
| Total | 74.278 (1) | 73.484 (3) | 60.396 (9) | 73.647 (2) | 60.106 (10) | 69.360 (5) | 67.677 (6) | 67.629 (7) | 73.376 (4) | 62.326 (8) |

*Note*: The entries denote the defuzzified performance value by using BNP, and the numbers in parentheses denote the order of performance values of the criteria.

further checking the relationships between the MDS dimensions and the six characteristics, it would make sense to label the two MDS dimensions ‘‘perceived fit of expatriation’’ and ‘‘attractiveness of host country’’, based on which, the perceived differences in preference among the host countries would be easy to interpret.

The scatter plot resulting from MDS (see Fig. 2) indicates that the preference distance between Japan and the US, based on the six aspects of expatriate assignment evaluation criteria, is very short (i.e., they are very similar). In other words, if we take ‘‘attractiveness of host country’’ and ‘‘perceived fit of expatriation’’ into account together, Japan and the US are

Table 3
The perceived values for the characteristics of criteria for each host country

| | Personal factor | Competence | Job characteristics | Family factor | Environmental factor | Organization relocation support |
|---|---|---|---|---|---|---|
| China | 15.305 | 16.840 | 15.637 | 9.520 | 8.654 | 8.412 |
| Japan | 15.298 | 13.654 | 15.834 | 9.519 | 10.162 | 9.018 |
| Thailand | 10.597 | 11.764 | 13.395 | 8.791 | 8.107 | 7.741 |
| The US | 14.906 | 14.128 | 15.966 | 9.340 | 10.472 | 8.835 |
| Mexico | 10.506 | 10.806 | 13.737 | 8.652 | 8.556 | 7.850 |
| The UK | 13.275 | 13.612 | 14.633 | 8.873 | 10.184 | 8.784 |
| Europe | 12.884 | 12.042 | 14.672 | 8.920 | 10.405 | 8.754 |
| Canada | 12.607 | 13.219 | 13.967 | 9.058 | 10.200 | 8.577 |
| Singapore | 14.236 | 15.533 | 15.083 | 9.360 | 10.571 | 8.592 |
| Korea | 10.915 | 10.842 | 13.981 | 8.859 | 9.362 | 8.367 |

Table 4
The Euclidean distance matrix of the 10 host countries

| | China | Japan | Thailand | The US | Mexico | The UK | Europe | Canada | Singapore | Korea |
|---|---|---|---|---|---|---|---|---|---|---|
| China | 0.000 | | | | | | | | | |
| Japan | 3.582 | 0.000 | | | | | | | | |
| Thailand | 7.365 | 6.165 | 0.000 | | | | | | | |
| The US | 3.337 | 0.747 | 6.153 | 0.000 | | | | | | |
| Mexico | 8.008 | 6.338 | 1.130 | 6.362 | 0.000 | | | | | |
| The UK | 4.295 | 2.451 | 4.187 | 2.238 | 4.463 | 0.000 | | | | |
| Europe | 5.775 | 3.204 | 3.642 | 3.210 | 3.516 | 1.634 | 0.000 | | | |
| Canada | 5.080 | 3.365 | 3.411 | 3.214 | 3.699 | 1.059 | 1.432 | 0.000 | | |
| Singapore | 2.625 | 2.366 | 6.117 | 1.809 | 6.571 | 2.289 | 3.799 | 3.079 | 0.000 | |
| Korea | 7.677 | 5.661 | 1.807 | 5.688 | 1.090 | 3.810 | 2.653 | 3.049 | 6.001 | 0.000 |

Table 5
Two-dimensional coordinates of the host countries resulting from MDS

| | Dimension 1 | Dimension 2 |
|---|---|---|
| China | 2.071 (1) | −0.859 (10) |
| Japan | 1.130 (3) | 0.686 (1) |
| Thailand | −1.694 (9) | −0.569 (9) |
| The US | 1.161 (2) | 0.467 (3) |
| Mexico | −1.920 (10) | −0.156 (7) |
| The UK | 0.212 (5) | 0.072 (5) |
| Europe | −0.379 (7) | 0.501 (2) |
| Canada | −0.207 (6) | −0.049 (6) |
| Singapore | 1.243 (4) | −0.276 (8) |
| Korea | −1.617 (8) | 0.183 (4) |

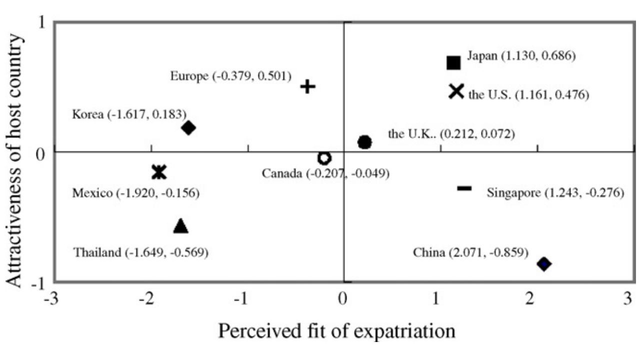


Fig. 2. Configuration for the preference similarity of the host countries resulting from MDS.

perceived by Taiwanese candidates as the most preferable destinations for expatriate assignments; while Mexico and Thailand are the least preferred destinations. For UK and Canada, the evaluators make no obvious preference in terms of

Table 6
Factor analysis results for the six characteristics

| Characteristics | Factor 1 | Factor2 |
|---|---|---|
| Personal factors | **0.889** | 0.445 |
| Competence | **0.932** | 0.081 |
| Job characteristics | **0.835** | 0.453 |
| Family factors | **0.931** | 0.255 |
| Environmental factors | 0.141 | **0.961** |
| Organization relocation support | 0.413 | **0.890** |

*Note*: The entries are varimax rotated factor loadings.

‘‘attractiveness of host country’’ and ‘‘perceived fit of expatriation’’, but they do perceive that Europe is a more attractive destination than UK or Canada. For Singapore and Korea, the evaluators make no obvious preference in terms of ‘‘attractiveness of host country’’, but there is a big difference in terms of ‘‘perceived fit of expatriation’’. Perhaps Singapore’s language and culture are perceived to be quite similar to Taiwan’s, and the expatriate candidates think they could adjust well there.

It is significant that China is ranked at first place in the ‘‘perceived fit of expatriation’’ dimension but last place in the ‘‘attractiveness of host country’’ dimension. China has the greatest perceived values of personal factors, competence, and family factors (see Table 2). As the best fit for working abroad destination, this is not surprising, because for a Taiwanese MNC the expatriate candidates will naturally perceive China as the most compatible destination for their international work experience and technical skills, since they are as well most qualified for the host language and the adjustment they need to undergo. In addition, the job characteristics are also a fit, and their family will support them the most, because their spouse could adjust there well.

As for the least attractive host country, although the cost of living in China is the lowest, candidates perceive that the standard of living, the medical facilities, and the educational facilities in China are quite awful. Furthermore, they do not think that their organization will give them adequate

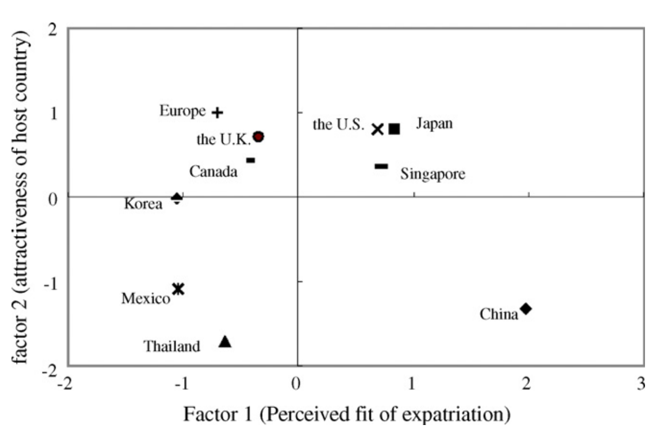


Fig. 3. Configuration for the preference similarity of the host countries in the factor space.

repatriation and career planning support. This means that the benefits from a low cost of living cannot compensate for the other disadvantages. From Table 1, we find that the ''perceived fit of expatriation'' dimension outweighs the other ''attractiveness of host country'' dimension. This is the reason why even though China is perceived as having a low standard of living and poor educational facilities and even though organization support such as repatriation or career planning support is not very good, it is still the most preferred host country in Table 2.

## 5. Conclusions

This paper uses fuzzy analytic hierarchy process (FAHP) to determine the weighting of subjective judgments and to derive the performance values of each alternative. Furthermore, MDS analysis is conducted to identify similar groups from distances among alternatives based on fuzzy preferences as perceived by the evaluators to obtain a clear visual dimensional map of a multi-criteria decision-making problem. The major advantage for decision makers is to get a clear snapshot of the alternatives. Moreover, after the reduced dimensions have been clearly explained and labeled, they could be treated as a mental shortcut for decision makers in the future. Finally, based on the measure of psychological distances, distinct clusters of alternatives could be obtained easily. To make a significant development in the soft computing field in the future, we could focus on applying the fuzzy input data without defuzzification to derive fuzzy MDS results.

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