Factor Analysis and Methods of Supplier Selection

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***Abstract*— We discuss in this paper the decision making in choosing the best alternative from some available options based on possibly a large number of selection criteria. This multi-criteria decision problem typically arises in supplier selection in supply chain management. Recently, there has been an increasing interest in the applications of dimensional reduction methods such as factor analysis to such decision processes. There are, however, a number of inherent issues and difficulties which have not been adequately addressed in the literature. For instance, there may be some criteria which load significantly on more than one factor. More importantly, it is seen in this paper that it is not always sensible to determine the importance of an identified factor according to its amount of shared common variance or explained variation. Similarly, attempts to routinely determine the local relative weight (within a factor) of importance of a criterion based on its factor loading or correlation with the factor may also lead to results in sharp contrast to those obtained from the experience of the practitioner. The present paper gives a simple, practical and easily implemented procedure to alleviate these difficulties. Although factor analysis is employed, it merely serves as a means of facilitating the direct rating of importance of each criterion and therefore does not experience the same difficulties of the classical factor analysis approach. Two examples are given to illustrate the proposed method and illustrate some potential problems of current approaches in the literature. The discussion in this paper will assist the practitioner in applying appropriately factor analysis in the decision procedure.**

Keywords – AHP, criterion weights, Factor analysis, multidimensional reduction, supplier selection

1. Introduction

Decision makers in many areas of business, administrative and social sciences are often charged with the responsibilities of selecting the best course of action that will meet a number (and often large) of criteria. This is typically true in Supply Chain management where supplier selection constitutes one of the most important organization activities. The selection of quality suppliers enables the firm to achieve an edge in a competitive business environment and is essential for the sustainability of a profitable business.

In general, the process of selecting suppliers involves the conceptual approach of identifying the appropriate selection criteria against which the potential suppliers are evaluated. In addition, the relative importance of each identified criterion must be determined and is often reflected in a certain numerical "weight". Each potential supplier is then evaluated by the decision maker using a combined score based on the scores obtained on the selected criteria weighted according to their relative importance. Recently, the use of dimensional reduction methods in supplier selection has garnered increasing attentions in the literature, especially in categorizing the selection criteria and weight assignments.

While the use of dimensional reduction method is potentially useful, its applications to supplier selection are not without problems. For instance, there may be some criteria which load significantly on more than one factor so that categorizing the criteria into mutually exclusive groups may not be feasible. More importantly, as seen in Sections 3 and 5, it is not always sensible to determine the importance of an identified factor according to its amount of shared common variance or explained

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variation. Similarly, determining the local relative weight (within a factor) of importance of a criterion based on its factor loading or correlation with the factor may also lead to results not necessarily in line with those based on the experiences of the practitioner or expert. These problems arise if the factor analysis is interpreted as a measurement model (of the underlying factors), as it will ignore the role of the specific factor (residual error) as measurement error when in fact the specific factor may represent characteristics of the criterion that is also important for the decision making. In Section 3, we discussed the major issues in these methods and suggest a new approach that circumvents these difficulties. To demonstrate the uses of the proposed method in general multi-criteria problem, we also discussed an example from recruitment data to illustrate the application of the proposed method.

2. Literature Review

Selecting the right supplier has direct influence on operating cost as well as the quality of the product or services provided by the firm [6, 1, 13, 19]. [11] showed empirically the importance of supplier selection in influencing business performance and also identified the major impacting factors that contribute to such relationship. The work of [24] and [12] also gave evidence the importance of supplier attitude and participation in building a long term relationship that benefits both the supplier and the firm. Because of the importance of supplier selection in supply chain management, considerable effort has been expended in the research community to develop analytical methods that could facilitate this multi-criteria decision process [22]. Criteria for selecting suppliers were discussed in [5, 15, 26, 16], among others. Considerable emphasis is also placed in the literature on categorizing selection criteria into major factors or constructs [16, 23, 4, 8]. [27] uses multivariate methods to examine the relationships among various selection criteria. Recently, there have been considerable interests in extending the analysis of supplier selection to include additional criteria for supplier selection in green supply chain management [9, 10].

In general, selection of supplier is a multi-criteria decision problem and therefore appropriate weighting of the relative importance and relevance of these criteria is central to the decision process. At a global level, industrial-wise determination of the importance and usefulness of these criteria is in general based on surveys of a large number of experts using typically dimensional reduction multivariate methods, such as factor analysis [18, 9, 10]. On the other hand, there is also an extensive literature on the methodologies for individual managers on assessing suppliers based on a set of identified criteria [3]. These methods include approaches that attempt to provide a simple, manageable and systematic procedure for weighting the importance of the selection criteria. These methods are summarized and reviewed in [20]. [25] gives an account of recent research activities in a wide variety of methodologies. One such methodology is the analytical hierarchical process, which breaks down the weight assignments to two or more levels, with smaller tasks involving fewer numbers of criteria at each level. Recently, the uses of dimensional reduction methods, such as factor analysis to create a hierarchical structure [18, 17, 21] have become increasingly popular. Some researchers [18] use further a second level of factor analysis treating the constructs as “items” and the latent variable that explains the common variances as a final “score” for comparing suppliers.

3. Methodology

Consider the general multi-criteria decision problem involving the selection of an optimal solution from a number of alternatives based on a potentially large number of relevant criteria. The determination of criteria for the selection process is assumed to have already been done based on the views and judgement of a subject matter expert(s) and is not the focus of our attention. Instead, a systematic approach for evaluating the available alternatives based on their scores on these criteria will be proposed, harnessing both the power of quantitative analyses and past experience and judgement of the decision maker. The steps involved are:

1. Employing dimensional reduction method, typically exploratory factor analysis, to identify a number of constructs. Unlike previous approaches (also see step 2 below) that use several individual single factor models, multi-factors in an integrated model (which allows a criterion to load on more than one factor) is permitted, broadening

substantially its scope of application and improving its goodness of fit.

2. Factor rotation performed to obtain interpretable factors which can later be used to check for consistence of importance values assigned to the selection criteria in step 3 below.
3. With references to a conceptual "performance score function", the decision maker assigns important values to the selection criteria based on the factors identified in steps 1 and 2, using a new, easily implemented procedure.

We now elaborate the 3 steps for multi-criteria decision and explain why some of the traditional methods have some potentially major issues that need to be carefully addressed. Many of the issues involved can be illustrated using a simple, easily understood example. The proposed method will then be applied to a supplier selection example discussed in [14]. Consider the following hypothetical situation where scores on four subjects - Mathematics, Physics, Chemistry and Biology, are obtained for a sample of 100 students. Suppose that the following sample correlation matrix is observed from the scores of the four subjects.

$$\begin{pmatrix} 1.0000 & 0.3800 & 0.1900 & 0.0950 \\ 0.3800 & 1.0000 & 0.8280 & 0.4800 \\ 0.1900 & 0.8280 & 1.0000 & 0.4450 \\ 0.0950 & 0.4800 & 0.4450 & 1.0000 \end{pmatrix}$$

An analysis of this correlation matrix results in a factor analysis model of two uncorrelated factors that can be used to reproduce the correlations among the scores of the four subjects. The factor loadings, uniqueness and communalities of the scores of the four subjects are given in Table 1.

Factor 1 loads heavily on all of the scores of the four courses except Math and therefore could be labelled as "general ability in mastering scientific concepts'. On the other hand, Factor 2 loads heavily on Math and could be seen as a student's "quantitative skill". We now show that how the evaluation, or the performance score, of each of the 100 students should be determined based on the factor model depends strongly on the purposes of the selection of the "best" student. In the first scenario, suppose that the purpose is to recruit the most suitable student to be trained as an assistant for a research project that requires quantitative statistical modeling of an environmental problem involving scientific concepts different from that of the four courses. Thus the emphasis is on the selected student's abilities in quantitative analysis and mastering scientific concepts. The performance score is purely a function of Factor 1 and Factor 2 only. Conditional on the values of the two factors, the conditional distributions of the scores of the four subjects carry no further relevant information. This is in line with the spirit of factor analysis as a measurement model where the interest is in measuring the underlying constructs and the residual (specific factor) in each of the equation in

Table 1. Factor model of the correlations

Subject	Factor 1	Factor 2	Unique -ness	Commu- nalities
Math	0.00	0.95	0.0975	0.9025
Physics	0.88	0.40	0.0656	0.9344
Chemistry	0.85	0.20	0.2375	0.7625
Biology	0.50	0.10	0.7400	0.2600
Variation explained	1.75	1.11		

the factor analysis model is purely seen as a measurement error that does not carry any further information about the constructs studied. In this case, it is only necessary to assign relative weighting to each of Factor 1 and Factor 2. In the second scenario, suppose the purpose is to award a scholarship to the best-performing student. The performance score is directly a function of the scores of the four subjects obtained by the student. In contrast to the previous scenario, weightings should be assigned directly to the four subjects, and categorizing the subjects into factors is not necessary and may not be most appropriate. In vendor selection, it is therefore generally not valid to measure the local importance (within a category/factor) of a criterion by measuring its loading (correlation) with the factor [17] as this would omit the useful information specific to this particular criterion. In addition, further difficulties in using factor analysis for vendor selection or general business decision problem may also arise when some criteria load on more than one factor as seen in the example in Section 4. Even if a factor analysis approach is applicable, the importance of the identified factors should not be based on their correlations (loadings) with a higher level common factor [18] as it may again ignore the useful information in the specific factor leading to conclusions far different from those based on the practitioners' judgement and experience, as seen in the example in Section 5. The fact that identified factors/ constructs that have little shared variances only implies that they have characteristics distinct from other constructs, but they may still represent important decision criteria. In point of fact, the identified constructs may be statistically independent (see Section 5) so that an analysis based on common variances at the higher level factor model may not even be possible.

Despite the shortcomings of the methods proposed in the literature as pointed out above, dimensional reduction method remains an interesting approach that could greatly facilitate the criteria weighting assignments in a multi-criteria decision exercise. When properly applied, they can substantially reduce the burden of the decision maker in subjective weighting of a large number of criteria and yield results of greater internal consistence. Let x_i be the score on the ith criterion of an alternative (vendor) and $x = (x_1, \dots, x_p)'$ where p is the number of criteria. Traditionally, the final score computed for each alternative or candidate is a weighted average of the x_i, This amounts to assuming that the performance function $p = \beta' x$ is linear in *x*, with the vector $\beta = (\beta_1, \dots, \beta_p)'$ normalized so that the components of β sum to 1. The function ***p*** can in fact be rescaled in any manner since the purpose is only to compare the final scores of all the alternatives. We find it more convenient by scaling the function ***p*** so that the largest β_i is equal to 1. The value β_i reflects the importance or how much the ith criterion weights on the final performance score. Thus when we say a certain criterion is twice as important as another one, we are merely saying that its β value is twice that of the other. The decision maker contributes to the decision process by providing judgemental input values for the β_i. To facilitate this process, suppose that the correlations among the x_i, can be explained by a factor model

$$x = \Lambda f + e$$

where $f = (f_1, \dots, f_a)'$ and *a* is the number of factors. One can use a rotational method such as the Quartimax to obtain factors such that each x_i loads on as few factors as possible. For the j^{th} factor, $j = 1,\dots,a$, let *Sj* be the collection of criteria x_i for which the highest factor loading occurs with the factor f_j. The decision maker is asked to identify the most important and the least important criteria in each *Sj*. Thus there are *2a* criteria selected. In the first stage of rating, the decision maker assigns importance (value of β) to these *2a* criteria. Instead of having these importance values summing to one, they are rescaled so that the highest importance is equal to 1. Denote the set of ordered criteria (ordered by their importance in descending order) by $C = \{C_1,\dots,C_{2a}\}$. For each *Sj*, let $C_{(j)}$ be the ordered subset$\{C_{j1},\dots C_{jn_j}\}$ of C where C_{j1} and $C_{jn_j}$are respectively the most important and least important criteria in *Sj*. In the second stage of rating, each criterion in *Sj*, excluding those already in *C*, is compared sequentially with $C_{j1},\dots C_{jn_j}$ starting with C_{j1} to identify two neighbouring criteria$C_{(j)1}$and $C_{(j)2}$ such that the criterion considered is either considered to be as important as $C_{(j)1}$ or less important than $C_{(j)1}$but more important than $C_{(j)2}$. In the first case, the criterion considered will be given the same importance value as that of $C_{(j)1}$. In the second scenario, the decision maker will assign an importance value that is the average of those of $C_{(j)1}$and $C_{(j)2}$ (or any intermediate value assigned by the decision maker). These procedures will be illustrated with an application in the next section. As a by-product, this importance value assignment procedure also yields importance values for the identified factors. To see this, observe that

$$p = \beta' x = \beta'(\Lambda f + e) = \alpha' f + \beta' e$$

where $\alpha' = (\alpha_1, \dots, \alpha_a) = \beta' \Lambda$ and α_j reflects the impact or importance of the j^{th} factor in determining the final performance score *p*. It is noted that the present approach does not attempt to assign importance weights based on the amount of shared common variances, the potential problem of which has been pointed out above. Rather, the weights are assigned through the two stages of rating based on the decision maker's valuable past experiences and knowledge.

4. A human resource example

To illustrate the methodology discussed in Section 3, we analyze here the application discussed in [14]. [14] examined the data collected by the Human Resources Department of a large firm responsible for selecting from 48 applicants a candidate to fill in a certain position. Part of the selection process involves interviews of these candidates by the same panel of four executives. The panel would rate each candidate on 15 attributes based on the candidate's responses during the interview. These 15 attributes are:

X1: Form of an application letter
X2: Appearance
X3: Academic ability X4: Likeability
X5: Self-confidence X6: Lucidity
X7: Honesty X8: Salesmanship
X9: Experience X10: Drive
X11: Ambition X12: Grasp
X13: Potential X14: Keenness to join
X15: Suitability

The sample correlation matrix of these ratings is also reproduced in [2, P435]. The following steps of analysis as suggested in Section 3 are performed.

Step1: Factor analysis using SPSS is conducted, yielding the results in Table 2:

Table 2. Eigenvalue analysis.

Total Variance Explained

Factor	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %	Rotation Sums of Squared Loadings Total	Rotation Sums of Squared Loadings % of Variance	Rotation Sums of Squared Loadings Cumulative %
1	7.504	50.027	50.027	4.500	30.002	30.002	5.542	36.945	36.945
2	2.061	13.743	63.770	3.967	26.447	56.449	2.477	16.510	53.456
3	1.468	9.785	73.554	1.615	10.764	67.213	2.139	14.263	67.719
4	1.209	8.061	81.615	1.090	7.267	74.480	1.014	6.761	74.480
5	.741	4.943	86.558						
6	.484	3.227	89.785						
7	.344	2.294	92.079						
8	.310	2.068	94.147						
9	.260	1.731	95.878						
10	.206	1.372	97.250						
11	.151	1.006	98.256						
12	9.33E-02	.622	98.878						
13	7.63E-02	.509	99.386						
14	5.77E-02	.384	99.771						
15	3.44E-02	.229	100.000						

Extraction Method: Maximum Likelihood.

Using Kaiser's rule, four factors with eigenvalues greater than 1 are selected. The scree plot (Figure 1 below) also suggests the same thing.

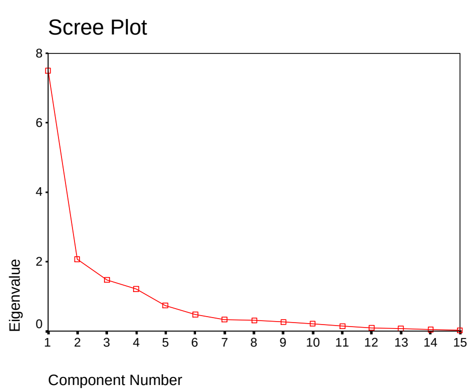

Figure 1. Scree plot of hiring data

Step 2. The initial factor obtained in 1) is rotated to obtain a more interpretable solution (Table 3). Note that there are items that load on more than one factor. For instance, X14 loads on Factors 3 and 4. Thus the present example does not meet the assumption in traditional approaches that each item measures only a single factor. This assumption, however, is not needed in our suggested method. Factor 1 loads on X2, X5, X6, X8, X10 to X13 which [2, P434] labelled it as "extroverted personality". Factor 2 loads on X1, X9 and X15 and may be labelled as "suitability". Factors 3 and 4 load on, respectively, X4, X7, X14 and X3, X14 and can be seen as what [2] called "agreeable personality" and "academic" ability.

Table 3. Final rotated factors of the hiring data

Rotated Factor Matrix[a]

	Factor			
	1	2	3	4
X1	.126	.727	.113	-.114
X2	.454	.139	.243	.172
X3	7.10E-02	.126	-1.2E-03	.674
X4	.227	.241	.829	-5.3E-02
X5	.922	-9.9E-02	.146	-8.4E-02
X6	.842	.118	.289	5.40E-02
X7	.248	-.228	.752	-1.7E-02
X8	.897	.236	7.52E-02	-6.7E-02
X9	9.16E-02	.767	-4.9E-02	.172
X10	.762	.393	.183	-5.6E-02
X11	.898	.190	.110	-6.3E-02
X12	.782	.282	.364	.159
X13	.724	.353	.449	.263
X14	.419	.393	.566	-.591
X15	.362	.766	5.03E-02	.136

Extraction Method: Maximum Likelihood.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Step 3: Importance value assignments. For each item X1 to X15, we determine which of S_j it falls into by identifying the factor which it has the highest loading with. For instance, X1 has the highest loading with Factor 2 and belongs therefore in S_2. Proceeding in this manner, we have the four sets:
S_1 = { X2, X5, X6, X8, X10, X11, X12, X13}
S_2 = {X1, X9, X15}; S_3 = {X4, X7}; S_4 = {X3, X14}

The Decision maker feels that among candidates with the same values of the factors, those with higher salesmanship (higher value of the specific factor corresponding to salesmanship) are most preferred compared with other items in S_1. Thus X8 is identified as the most important item in S_1. Suppose that the most important and least important items identified by the decision maker are as given in Table 4.

Table 4. Most and least important items in each of S_1 to S_4.

Set	Most important	Least important
S_1	X8 (salesmanship)	X11 (ambition)
S_2	X15 (suitability)	X1 (application letter)
S_3	X7 (honesty)	X4 (likeability)
S_4	X3 (academic ability)	X14 (keenness to join)

Table 5 lists the eight items in Table 4 in descending orders along with the importance values assigned subjectively.

Table 5. Assigned weights

item	X15	X8	X7	X4	X3	X14	X11	X1
Importance value	1	1	.25	.2	.17	.15	.1	.1

Consider now other items not in Tables 4 and 5. Take for example, X2 (appearance) in S_1. Then $C_{(1)}$ = {X8, X7, X4, X3, X14, X11} and X2 is considered to be less important than X4 but more important than X3 and is assigned an importance value of (.2 + .17)/2 = .185. The complete list of importance values are given in Table 6. Given the values of X1 to X15 for any given candidate, these importance values can be used to compute the final score of that candidate.

Table 6. Assigned importance values of the 15 items

Item	X1	X2	X3	X4	X5	X6	X7	X8
Importance value	0.1	0.185	0.17	0.2	0.1	0.185	0.25	1.0
Item	X9	X10	X11	X12	X13	X14	X15	
Importance value	0.8	0.185	0.1	0.125	0.1	0.15	1.0	

Using the formula $\alpha' = \beta'\Lambda$, it is found that $\alpha' = (2.26, 1.96, 0.78, 0.27)$, or in terms of relative weightings, 0.43, 0.37, 0.15, and 0.05 for respectively factors 1 to 4. Had the weightings been based on the common variances of the factors from Table 1, the relative weightings would have been equal to 0.61, 0.17, 0.12, and 0.10.

5. A supplier selection example.

[7] reported and analyzed data collected from a sample of subjects responding to a questionnaire regarding their views about the importance of each of nine supplier selection criteria in selecting providers for part or the entire information system for a company. These criteria were determined and selected for study based on the authors experience, practitioners' views and review of the relevant literature. The importance as expressed by each respondent is given on a nine-point scale; for details, See [7]. As part of the analysis, [7] performed a factor analysis on the data and successfully identified three statistically independent factors which can be interpreted as F1: Product/service attributes, F2: Vendor attributes and F3: Economic attributes. The eigenvalues obtained are 3.76, 1.49 and 1.11 for respectively F1 F2 and F3. Thus the relative weighting attached to each factor is traditionally calculated as eigenvalue/(sum of eigenvalues), yielding weights of 0.591, 0.234, 0.175 for respectively F1 F2 and F3. For local relative weight u_{ij} of the i^{th} selection criterion within the j^{th} factor that is determined by its factor loading [17], it is calculated as $l_{ij}/\sum_i l_{ij}$. The global relative weight is then found as $w_{ij} = m_j u_{ij}$, where l_{ij} is the loading of the i^{th} selection criterion for the j^{th} factor and m_j is the relative weight of the j^{th} factor. Results of the calculations based on Table V of [7] are given in Table 7, along with the rankings of the criteria based on the w_{ij} and those from the study of [7]

Table 7. Rankings of criteria based on factor loadings and views of practitioners

Selection criteria		Practitioners' global ranking	Global ranks	Local ranks within factor
F1: Product/service attributes				
	Flexibility	1	4 (.115)	1
	Ease of use	2	5 (.114)	2
	Integration with existing applications	6	6 (.110)	3
	Integration with existing database	7	7 (.103)	4
	Efficiency	4	8 (.076)	5
	Ease of installation	8	9 (.074)	6
F2: Vendor attributes				
	Vendor support	5	2 (.118)	1
	Vendor viability/reliability	3	3 (.116)	2
F3: Economic attributes				
	Cost	9	1 (.175)	1

Two important points are in order. First, the three identified factors are statistically independent so that the relative importance of the three factors cannot be determined by the amount of shared common variances as in [18]. This is a good illustration of the potential problem of using high level of factor analysis model treating "appropriateness of supplier" as the single underlying factor (and factors identified in the low level model as the "variables" in the high level factor model). As explained in section 3, this is due to the fact that the residual errors (specific factors) also contain relevant information in addition to what is contained in the common factor. Second, it is seen that the rankings (based on the global weights w_{ij}) by the entirely automated procedure based on factor analytic model are markedly different from those determined in a survey incorporating the experiences and expertise of the practitioners interviewed. The criterion "cost", while rated as the least important by the practitioners, actually has the greatest weighting by the factor analysis approach. Even within the same factor "Product/service attribute", the criterion "efficiency" is ranked third, but fifth by the factor analysis approach. Again, the factor analysis approach only takes into account the amount of shared variance component, but not information in the specific factor (residual term) considered to be relevant in supplier selection by the practitioner.

6. Conclusions

Factor analysis is a common approach for the decision process in selecting suppliers. It is particularly useful in creating a hierarchy of factors and subcriteria and thereby reducing the dimension of pairwise comparisons. However, its uses are not without restriction and its routine application is not recommended. An inherent difficulty that may arise in some applications stems from the possibility of cross loading with a criterion loads on more than one factor. The process of grouping or categorizing the criteria requires that each criterion be included in one and only one factor. More importantly, importance of the factors should not be based on the associated explained variation. Furthermore, the weightings of the criteria should not be proportional to their loadings as the residual term may also include important information for the decision process. We address in this paper these issues and propose a simple, practical and easily implemented procedure that assigns importance value to each of the decision criteria directly, using a factor analysis approach only as a means of facilitating the rating process. The input of the practitioner is incorporated into the process which is more preferable to automated procedures that require little human intervention. The method alleviates some of the shortcomings of some traditional approaches, requiring less rigid restriction for it to be operational. The proposed procedure reduces the amount of pairwise comparisons of the criteria, but still leaves enough room for input from the decision maker based on the person's skill and past experience.

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