Developments in Statistics and Methodology
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Metodološki zvezki, 9, Ljubljana: FDV 1993

Comparative Studies Methodology-Clustering Approaches

The Case of Motivation Items in USA, Japan and Slovenia

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Abstract

Comparative studies are often used in social science research. Allardt (1990) argues that quantitative analysis is usually at its best at the explorative stage of a comparative study. This paper discusses three types of clustering approaches which may be used at this stage of a comparative research (Ferligoj 1992).

The first one deals with comparisons of the typologies of variables. The typologies can be obtained by standard clustering algorithms (e.g., Gordon 1981, Anderberg 1973, Everitt 1974). The problem arises when the researcher wants to compare the obtained clusterings (e.g., partitions, hierarchies). One possible solution is using a multicriteria clustering approach (Ferligoj & Batagelj 1992).

The main idea behind the second approach is to first find the structure of units when all countries are considered together (clustering of stacked data). This can be done through the use of the leader algorithm. The problem in this approach is that we usually have a different number of units per country (larger samples have stronger influence on the clustering solution). Therefore we propose to draw samples of the same size of the units of each country and stack them together. Sampling and clustering should be done several times to check the stability of the solution. The obtained representatives (leaders) can be used as the initial set of leaders for clustering units of each country separately. One can calculate the value of the structure enforcement coefficient, (Ferligoj 1986), for each country and thus obtain the fit of each country to the structure of all countries.

The third approach deals with between-country comparisons. At this stage we propose to fix number of clusters to obtain optimal clusterings of the units in each country. In further analysis one can compare the obtained clusterings with clustering approach.

All mentioned clustering approaches are used for the analysis of motivation items in three countries: USA, Japan and Slovenia. In all three countries undergraduate students were asked about different motivations for later employment.

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Keywords: Clustering of the stacked data; Explorative stage; Enforcement coefficient; Hierarchical agglomerative algorithm; Leader algorithm; Sampling; Standarization; Multicriteria clustering.

Acknowledgements: The authors are grateful to the editors, the reviewers, and to prof. dr. Anuška Ferligoj for suggestions leading to an improved article.

1 Introduction

The goal of this paper is to present three different clustering approaches which can be fruitfully used at the explorative stage of comparative studies. Therefore we briefly consider general methodological issues of comparative research, we describe the proposed clustering approaches and apply them to analyze the motivation items for later employment in USA, Japan and Slovenia. At the end we draw some conclusions and look beyond the explorative stage of comparative research and beyond the quantative approach.

2 Methodological issues of comparative research

At the beginning of this article we would like to stress the most important general methodological issues of comparative studies (e.g. Oyen 1990, Rokkan 1968, Scheuch 1989 and Wellhofer 1989). They are listed below in random order.

1. *EQUIVALENCE OF MEANINGS IN TRANSLATION:* The main problem as far as translation is considered is the equivalence of meanings. The concepts behind words are often different in different languages. Certain terms may have emotional meanings in one society and non-emotional in another. The formats of questions may carry cultural implications and therefore some questions may appear quite silly when transmited into the language of another society. One of the problems is also that questions are being answered, although they mean quite different things to different respondents.

2. *EQUIVALENCE OF INDICATORS:* Social scientists are used to considering questions as indicators which have probabilistic relationships to the properties measured. So, questions are comparable not if they are identical in their common sense meanings but when they are functionally equivalent according to the purposes of analysis.

3. *DESIGN OF A REPRESENTATIVE SAMPLE:* The quality of samples effects the results of comparative studies. The general problem of how to design a good representative sample is particularly delicate when there is no adequate sampling information available (e.g. when the developing countries are considered).

4. *DEFINITIONS OF CONCEPTS USED:* What is taken for granted in a certain country does not necessary exist or appear in another country. A certain concept may be important for one researcher and completely irrelevant for his colleague from another country.

5. *GALTON'S PROBLEM:* So called Galton's problem appears when the variation (of the observed variables) within the country is greater than the variation between

countries. The reverse problem appears when the causative element is a part of much larger geographical context then covered in a particular research (no variation within or between countries).

6. INFLUENCE OF THE CULTURE: The researcher can never succeed completely in freeing himself of the dominant attitudes, presumptions, opinions, values and prejudices of his own culture.

7. THE MEANING OF "NATION" AS A VARIABLE: The question is, does nation or nationhood means anything in the specific context. If we want to use nation or nationhood as an explanatory variable we have to go deep into theory and clearly define all causes and intercauses involved. Nothing can be taken as granted in advance!

We have only briefly considered the most important general methodological issues of comparative research. We are aware, that there are many other salient issues, which are not explicitly listed in this chapter. But, the further consideration of general methodological issues of comparative research is not the purpose of this paper.

In the paper we concentrate on quantative approaches. Allardt (1990) argues that quantitative analysis is usually at its best at the explorative stage of the comparative study. In the next part of the paper we discuss three types of clustering approaches which may be fruitfully used at this stage of a comparative research.

3 Clustering Approaches in comparative studies

3.1 Basic Notions

The purpose of cluster analysis (or classification) is to investigate the structure within the set of objects, in particular, to ask whether the objects fall naturally into a certain smaller number of groups (or clusters) of objects, such that objects within a group are "similar" to one another.

Clustering problem can be formulated as an optimizational problem: Determine the clustering C* for which

$$P(C^*) = \min_{C \varepsilon \Phi} P(C)$$

where Φ is the set of feasible clusterings (e.g., partitions, hierarchies), C is a clustering of a given set of units E, and P is the criterion function. In the case of partitions into k clusters, the Ward criterion function is usually used

$$P(C) = \sum_{c \varepsilon C} \sum_{X \varepsilon c} d(X, Tc)$$

where c is a cluster, Tc the centroid of the cluster c, and d the squared Euclidian distance.

In general, the clustering problem is NP-hard problem (NP means Nondeterministic Polynomial). This is the reason why different heuristic algorithms for producing "good" clustering solutions have to be used.

The following algorithms are used in this paper:

* **the hierarchical agglomerative algorithm** (e.g. Anderberg 1973, Everitt 1974, Gordon 1981)
* **the leader algorithm** (e.g. Anderberg 1973, Everitt 1974, Gordon 1981)
* **multicriteria clustering algorithms** (Batagelj & Ferligoj 1990, Ferligoj & Batagelj 1992)

All computations were carried out with the clustering package "Cluse-TV" (Batagelj 1992).

3.2. The proposed clustering approaches

The algorithms listed above are used to construct three different clustering approaches (Ferligoj 1992), later applied to analyze motivation items in USA, Japan and Slovenia. Below we briefly consider each of the three approaches.

3.2.1. COMPARISON OF TYPOLOGIES OF VARIABLES: The typologies can be obtained by standard clustering algorithms. The problem arises when the researcher wants to compare the obtained clusterings. One possible solution is using a multicriteria clustering approach.

3.2.2. THE STRUCTURE OF UNITS ACROSS COUNTRIES: The main idea behind the second approach is first to find the structure of units when all countries are considered together (clustering of stacked data, common solution). This can be done by the leader algorithm. The problem in this approach is that we usually have a different number of units per country. Therefore we propose to draw samples of the same size of the units of each country. Sampling and clustering should be done several times to check the stability of the solution. The obtained common leaders (representatives) can be used for classification of the units of each country separately to the nearest leader. The fit of a particular country to the common solution can be obtained.

3.2.3. BETWEEN - COUNTRY COMPARISON OF CLUSTERINGS OF UNITS: At this stage we propose to fix the number of clusters, to obtain optimal clusterings of the units in each country. The between - country comparison can be done with clustering of country representatives (leaders).

4 Application of the proposed clustering approaches - analysis of the motivation for later employment in USA, Japan and Slovenia

4.1 Motivation - some theoretical considerations

Since we analyze the motivation items, we have to explain the concept of motivation first.

Motivation denotes the explanation of reasons for behaviour. It is influenced by the object of intention, i.e. the motive. Explanation of motivation to a large extend depends on cultural and historical state of particular society and on stage of human nature and social relations.

In our analysis we concentrate on motivation for later employment and obtain it with the attitudes toward the following statements (Murrell, Frieze and Frost 1991):

4.2 Statements:

1. *CAREER:*
   After graduation, it is important to me that I have a career, not just a job.
2. *RECOGNISED:*
   It is important to me that I become recognised in my field of work.
3. *THE BEST:*
   It is important to me that I become one of the best in my field of work
4. *HELP OTHERS:*
   I want a job that will allow me to help others
5. *PAY WELL:*
   I want a job that will pay well.
6. *FLEXIBILITY:*
   My ideal job would allow me great flexibility in setting hours and deciding what to do each day.
7. *FAMILY:*
   It is important to me that my job allow plenty of time for me to be with my family.

The short variable names used later in the results are printed in capital letters in front of the statements.

Attitudes toward these statements have been measured on 5 point scales with middle point; from 1 "strongly disagree" to 5 "strongly agree". The higher the value, the stronger the agreement.

4.3 The data of three countries

The data are taken from "Cross Cultural Survey of Student's Attitudes" which was conducted by Irene Frieze, Anuška Ferligoj and Yasuko Morinaga in 1991. There are many batteries of questions included in this survey. We analyze only one, measuring

Table 1: Sample description

country	sample size	year
USA (PITTSBURGH)	155	1991
JAPAN (HIROSHIMA)	619	1991
SLOVENIA (LJUBLJANA)	157	1991

the motivation for latter employment. In all three countries only undergraduate students are included in the sample.

In the table below the samples are described. We analyze the samples of Pittsburgh, Hiroshima and Ljubljana students, which are not of the same size.

4.4 Results

4.4.1 Basics statistics

In the table below mean values and standard deviations of the chosen variables are reported for each country.

Table 2: Basic statistics

VARIABLES	USA	JAPAN	SLOVENIA
CAREER	4.38 .84	3.83 .99	3.97 .81
RECOGNISED	3.69 .90	4.25 .86	3.91 .72
THE BEST	3.75 .89	3.41 1.16	3.55 .87
HELP OTHERS	4.23 .74	4.07 .96	4.03 .81
PAY WELL	4.26 .68	4.07 .93	4.07 .81
FLEXIBILITY	3.78 .89	3.82 1.00	4.04 .89
FAMILY	4.05 .75	4.29 .90	3.50 .83

We can see in Table 2 that the standard deviations are not particularly large if compared to the mean values. The mean values vary from 3.5 (FAMILY in Slovenia) to 4.4 (CAREER in USA). The motivation of Pittsburgh students is on average higher. The variation between countries is large enough to make us believe that it is worthwhile to analyze differences and similarities between countries.

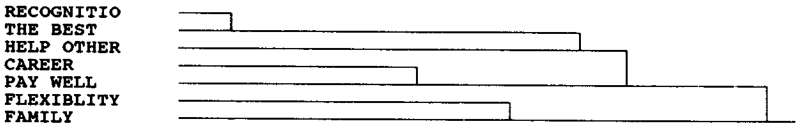
The basic statistics provide us with the first insight into the comparison of motivation items. We are continuing the analysis with clustering approaches. The first one deals with the comparison of variables.

4.4.2. Comparison of typologies of variables

If we want to compare typologies of variables, we have first to obtain the typology in each country separately. This can be done by standard clustering algorithms. The typologies presented below are obtained with the hierarchical agglomerative algorithm. The correlation coefficient is used as a measure of similarity between variables.

Because the Ward method is used to obtain hierarchies, dissimilarity is computed from the correlation coefficient ((1 - r)/2).

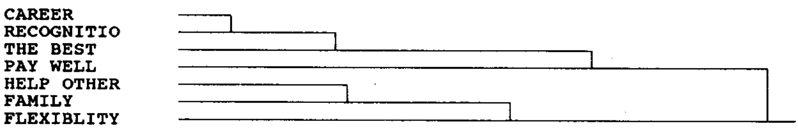
USA



Cluster 1:		Cluster 2:	
	CAREER		FLEXIBLTY
	RECOGNITIO		FAMILY
	THE BEST		
	HELP OTHER		
	PAY WELL		

Figure 1: Typology of variables in USA.

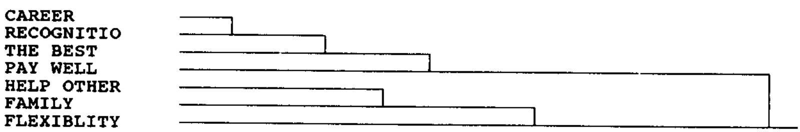
JAPAN



Cluster 1:		Cluster 2:	
	CAREER		HELP OTHER
	RECOGNITIO		FLEXIBLITY
	THE BEST		FAMILY
	PAY WELL		

Figure 2: Typology of variables in Japan.

SLOVENIA



Cluster 1:		Cluster 2:	
	CAREER		HELP OTHER
	RECOGNITIO		FLEXIBLITY
	THE BEST		FAMILY
	PAY WELL		

Figure 3: Typology of variables in Slovenia.

In each country there are two distinct groups (or clusters) of variables. We find two types of variables in each country.

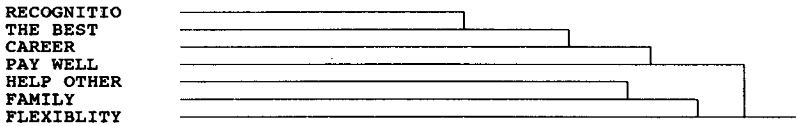
Two of the three typologies are the same. We find the same variables in Japan and Slovenian clusters. In the first cluster we find variables measuring success in public or business sphere: CAREER, RECOGNITIO, THE BEST and PAY WELL. In the second cluster we find variables measuring orientation in private sphere: HELP

OTHER, FLEXIBILITY and FAMILY. The USA typolgy is slightly different. The variable HELP OTHER is in the first cluster. It seems that HELP OTHER is part of the success in public or business sphere in USA.

We are not interested just in typologies of variables obtained in each country separately. In the previous paragraph we have already compared the obtained typologies between countries by "eyeballing". Now we want to compare the typologies across countries.

We believe that the best way to achieve that goal is to use multicriteria clustering algorithms (Ferligoj & Batagelj 1992 and Batagelj & Ferligoj 1990). This algorithms enable us to obtain "common" solution by clustering variables of each country simultaneously. We simultaneously consider three data matrices and look for the best "common" solution.

Below we present "common" dendrogram obtained with Multicriteria hierarchical agglomerative algorithm, Maximum method and Horwicz's rule. Eucledian distance is used as a measure of dissimilarity. Wald's and Laplace's rules provide us with the same results.



Cluster 1:	RECOGNITIO THE BEST CAREER PAY WELL	**Cluster 2:**	HELP OTHER FAMILY FLEXIBLITY

Figure 4: Typology of variables - 'common' dendrogram.

From the figure above it can be seen that the "common" typology is the same as those obtained in Japan and Slovenia.

Pareto clusterings (a clustering is Pareto efficient if it can not be improved on any criterion without sacrificing some other criterion) into two clusters, obtained with Multicriteria nonhierarchical clustering algorithm, provide us with two different typologies: one is the same as in Japan and Slovenia and the other one is the same as in USA. Pareto clusterings into three clusters provide us with six different solutions.

So far we have been interested in typologies of variables. The other two clustering approaches deal with the structure of units. The first of the two deals with the structure of units across countries and the fit of a particular country to the "common" structure.

4.4.3 Structure of units across countries

To obtain the structure of units across countries standard clustering algorithms can be used, but the number of units per country must be the same. Larger samples have stronger influence on clustering solutions. As you can remember Japanese sample is four times as large as Slovenian or USA sample.

In this analysis, to obtain the same number of units per country, 100 random samples of 150 units are drawn from units of each country. So we obtain 300 samples of the same size (100 per country). We stack them together into 100 stacked data matrices, each of which is constructed of one random sample of Japanese units, one random sample of USA units and one random sample of Slovene units. So, in each stacked data sample there are 450 units, 150 of each country. The whole procedure is presented in the figure below.

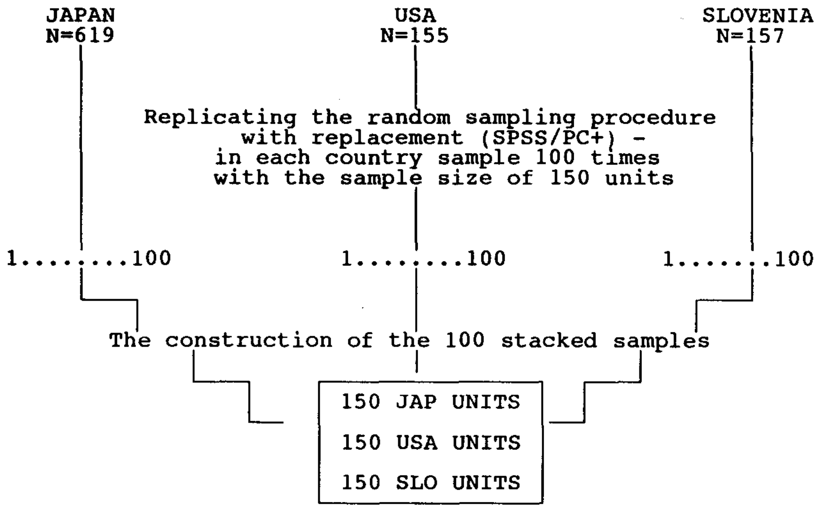


Figure 5: Sampling procedure.

In the next step the units of each stacked data matrix are clustered into optimal number of clusters by leader algorithm. Previous analyses have determined that the optimal number of clusters is six. So, for each stacked sample, six leaders (or representatives) of the best clustering and the value of the belonging Ward criterion function are obtained.

Both statistics vary from stacked sample to stacked sample because of the two reasons. The first reason is **sampling effect**: different subsamples have different structure. The second reason is **local optima effect**: optimization of the Ward criterion function stops before obtaining global optima.

The variation can be presented by mean and standard deviation of obtained Ward criterion function, measured on each stacked sample:

MEAN	1530.02
STD. DEV.	44.74

It can be seen that the standard deviation is low if compared to the mean. That means that sampling effect and local optima have in average only very limited influence on the obtained clusterings.

To analyze the variation of the leaders obtained for each stacked sample a new stacked data matrix, consisting of all obtained leaders, is constructed. It is presented in the figure below:

```
6 LEADERS    1
    .        .
    .        .
    .        .
    .        .
    .        .
    .        .
6 LEADERS   100
```

Figure 6: Stacked leaders (100 * 6 = 600)

If all 100 clustering solutions were the same, we would have 6 times 100 exactly the same leaders (because all first leaders would be the same, all second leaders would be the same,..., and all sixth leaders would be the same).

Due to the sampling effect and local optima effect, the sets of leaders are not exactly the same. We analyze the stacked leaders matrix by the leader algorithm to study the stability of the obtained clustering solutions. The results are presented in the table below.

Table 3: Number of leaders in the each cluster

CLUSTERS	EXPECTED #	OBSERVED #	DIFF.
CLUSTER 1	100	94	- 6
CLUSTER 2	100	99	- 1
CLUSTER 3	100	102	+ 2
CLUSTER 4	100	100	0
CLUSTER 5	100	96	- 4
CLUSTER 6	100	109	+ 9

From the table it can be seen that the sets of leaders are not exactly the same. But the difference is not frustrating - only 11 leaders (1.8%) are misclassified.

The six leaders, obtained from stacked leaders matrix, represent the structure of units across the countries. It is important to notice that the leaders are mean values of group representatives on motivation variables. According to these mean values, each leader can be given a name. We name the leader with lowest mean values on nearly all variables **"The least motivated type"**; the leader with highest mean values on nearly all variables is named **"Highly motivated type"**. The leader with low mean values on "success in public or business sphere" variables and high mean values on "orientation in private sphere" variables is named **"Family type"**; the leader with reverse values is named **"Individual type"**; and the two leaders with average mean values on all variables expect FLEXIBILITY are called **"Flexible type"** if the mean value on this variable is high and **"Nonflexible type"** if the mean value is low. The leaders are reported in the table below.

Table 4: Common leaders; mean values of group representatives on motivation variables

	CAREER	RECOGN	BEST	HELP	PAY	FLEX	FAMILY	TYPE
L1	2.81	3.03	2.52	3.64	3.25	3.45	3.59	THE LEAST MOT.
L2	3.65	3.41	2.78	4.04	3.97	3.91	4.18	FAMILY
L3	4.03	3.79	3.55	4.17	4.15	4.43	3.76	FLEXIBLE
L4	4.28	4.00	3.79	4.34	4.17	2.77	3.85	NONFLEXIBLE
L5	4.53	4.36	4.09	3.21	4.40	4.05	3.20	INDIVIDUAL
L6	4.68	4.74	4.54	4.62	4.36	4.42	4.59	HIGHLY MOTIVAT.

Fit to the structure of units across countries

The units of each country can be classified according to the six common leaders, initial and best criterion function values can be computed, and the structure enforcement coefficient K (Ferligoj 1986) can be obtained to measure the fit of particular country to the common solution. The lower the value of the structure enforcement coefficient, the better the fit. The statistics is calculated as:

$$K = \frac{\text{initial criterion function - best criterion function}}{\text{initial criterion function}}$$

The results of classification, i.e. the percentages of units in each country classified to the six common leaders, and the values of structure enforcement coefficient per country are reported in the table 5.

It can be seen that the value of structure enforcement coefficient is the highest for USA. That means the sample from USA has the purest fit to the structure of units across countries. The fit of the other two samples is better and approximately the same.

We would like to stress the most important specifics of each country. In Slovenia are high percentages of "Flexible type" (27.4) and "Individual type" (20.4) students and low percentage of "Highly motivated" (8.9) students. In USA are high percentage of "Nonflexible type" (28.4) students and low precentages of "The least motivated type" (4.5) and "Individual type" (7.1) students. In Japan are high percentage of "Highly motivated type" (30.0) students and low percentage of "Flexible type" (11.0) students.

Table 5: The percentages of units in each country classified to the six common leaders and the values of structure enforcement coefficient K

COMMON LEADERS	SLOVENIA	USA	JAPAN
THE LEAST MOTIVAT	10.8	4.5	12.3
FAMILY TYPE	20.4	16.8	17.3
FLEXIBLE TYPE	27.4	21.3	11.0
NONFLEXIBLE TYPE	12.1	28.4	18.0
INDIVIDUAL TYPE	20.4	7.1	11.5
HIGHLY MOTIVATED	8.9	21.9	30.0
K	.13	.18	.12

4.4.4 Between-country comparison

The third, and the last approach deals with between-county comparisons. We have first to obtain the optimal clusterings of the units of each country. This can be done by standard clustering algorithms. To enable the comparison, we propose to fix the number of clusters, i.e. to cluster the units of each country in the same optimal number of clusters. Previous analyses have determined that the optimal number of clusters is six.

For each country six leaders are obtained by leader algorithm. They are named with the same names as leaders in the second approach, i.e. "The least motivated type", "Family type", "Flexible type", "Nonflexible type", "Individual type" and "Highly motivated type". They are presented by stars in Figure 7. Each leader is represented by a star. Each shine or direction of a star represents a variable. The length of a shine depends on variable value. Variable values (i.e. mean values of group representatives) are normalised by the formula: (Max - Min)/2. In each column the three most similar leaders of different countries are printed.

We can compare the obtained leaders (stars) by "eyeballing". In that way differences and similarities between the leaders of different countries can be seen. But the whole picture is very complex. Therefore we propose to cluster the leaders into six clusters to obtain a clear picture. If the sets of leaders, printed in each column (leaders of three countries, presumably of the same type) were the most similar, we would have three leaders in each of the six clusters. From Figure 8 it can be seen that it is not the case in our analysis.

To cluster the best leaders of each country, the hierarchical agglomerative algorithm and the Ward method are used. As a measure of dissimilarity between objects, Euclidian distance is computed.

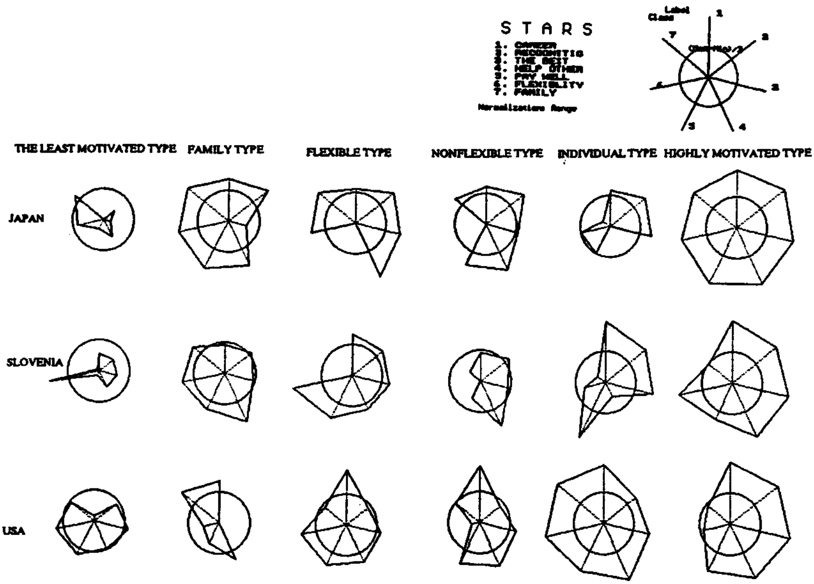


Figure 7: The best six leaders of each country.

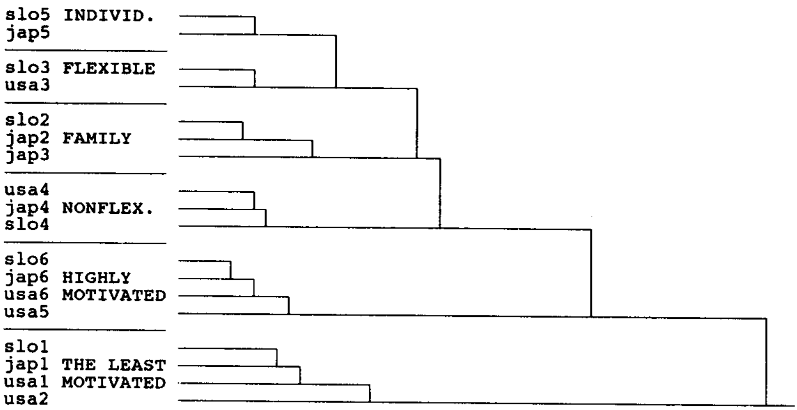


Figure 8: Dendrogram of the best six leaders of each country.

From the dendrogram above it can be seen that there are two, three or four leaders in each of the clusters. That means there are differences between countries. The types of leaders, which we have identified in the second approach and use again in this approach, are not the same between countries. The main differences are:

1. There is **no "Individualist type" in USA**, but there are **two "Highly motivated types"**. What we have considered as "Individualist type" in USA is more similar to "Highly motivated type" in USA, Japan and Slovenia than to "Individualist type" in Japan and Slovenia.

2. There is **no "Family type" in USA**, but there are **two "The least motivated types"**. What we have considered as "Family type" in USA is more similar to "The least motivated type" in USA, Japan and Slovenia than to "Family type" in Japan and Slovenia.

3. There is **no "Flexible type" in Japan**, but there are **two "Family types"**. What we have considered as "Flexible type" in Japan is more similar to "Family type" in Japan and Slovenia than to "Flexible type" in USA and Slovenia.

5 Discussion and conclusions

Various clustering approaches have been used to achieve the presented results. Similarities have been found and specifics of each country have been identified. But, which approach is the best? We propose to use all three approaches if possible. Different approaches investigate the structure of the data from different viewpoints. Thus, to get a complete picture, various approaches are required. If it is not possible to use various approaches or there is no need to investigate the problem from different viewpoints, the choice of the best approach depends on the problem under investigation. But, the comparisons of the obtained clusterings always demand that one not standarize variables before using clustering algorithms (Ferligoj 1992).

The salient problem of different number of units in the samples of different countries can be approached in at least two ways (Ferligoj 1992). The first way is to fix the number of clusters and compare the cluster representatives of each country. In that case, the number of clusters should be carefully chosen. The second way is to draw samples of the same size of the units of each country. In that case, the stability of the clustering solution should be checked.

So far we have not said anything about how the similarities and specifics found can be explained. To answer this question we should move beyond the explorative stage of the study and employ qualitative and quantitative methods to provide the final insight and understanding. Also, the measurement model should be reevaluated on the basis of deeper knowledge about countries and cultures considered.

So far the variable "country" has not been used as an explanatory variable. It has been used as a splitting line between units because we have been interested in comparisons between and across countries. Such a split is completely justified with the known theories of motivation. But if we want to use "country" or "nation" as an explanatory variable, we have to go deeper into theory and clearly define all causes and intercauses involved (e.g., social/individual context, motivation/behaviour linkage, goal/means connection etc.)

References

[1] ALLARDT E. (1990): Challenges for Comparative Social Research. *Acta Sociologica*, **33**, 183-193.

[2] ANDERBERG M.R. (1973); *Cluster Analysis for Applications*. New York: Academic Press.

[3] BATAGELJ V., and FERLIGOJ A. (1990); Agglomerative Hierarchical Multicriteria Clustering Using Decision Rules. In: Momirovič K., and Mildner V. (Eds): Proceedings of COMPSTAT'90, Heidelberg: Physica-Verlag, 15-20.

[4] BATAGELJ V. (1992): CLUSE for IBM PC - Manual. Ljubljana.

[5] EVERITT B.S. (1974): *Cluster Analysis*. London: Heinemann Educational Books.

[6] FERLIGOJ A. (1986): Clustering with Constraining Variable. *Journal of Mathematical Sociology*, **12**, 299-313.

[7] FERLIGOJ A. (1992): Clustering Approaches in Comparative Studies. Paper presented at colloquium 'Evaluating the validity and reliability of measurement of well-being in comparative studies using a structural modelling approach', Leuven.

[8] FERLIGOJ A., and BATAGELJ V. (1992): Multicriteria Clustering Algorithms. *Journal of Classification*, **9**, 43-61.

[9] GORDON A.D. (1981): *Classification*. London: Chapman and Hall.

[10] HARTIGAN J.A. (1975): *Cluster Algorithms*. New York: Wiley.

[11] MURRELL A.J., FRIEZE I.H., and FROST J.L. (1991): Aspiring to Careers in Male and Female Dominated Professions: A Study of Black and White College Women. *Psychology of Women Quarterly*, **15**, 103-126.

[12] OYEN E. (1990) (Ed.): *Comparative Methodology: Theory and Practice in International Social Research*. London: SAGE.

[13] ROKKAN S. (1968) (Ed.): *Comparative research across Cultures and Nations*. Paris: The Hague.

[14] SCHEUCH E. (1989): Theoretical Implications of Comparative Survey Research: Why the Wheel of Cross-Cultural Methodology Keeps on Being Reinvented. *International Sociology*, **4**, 147 - 167.

[15] WELLHOFER E.S. (1989): The Comparative Method and the Study of Development, Diffusion and Social Change. *Comparative Political Studies*, **22**, 315 - 342.