Identifying the component structure of job satisfaction by categorical principal components analysis

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Abstract

The component structure of a 14-item scale measuring different aspects of job satisfaction was investigated, and its stability among different types of organizations. The participants were 2066 workers from 220 organizations in the Italian social service sector. The job satisfaction items were measured at an ordinal scaling level and analyzed by Categorical Principal Components analysis (CATPCA) using monotonic (spline) transformations. The sample was randomly divided into a training set and a test set. CATPCA was applied to the training set and resulted in a two-component solution. Results of a Multiple Group analysis for the test set confirmed the validity of the training set solution. From the two-component solution, we extracted two subscales with reliabilities (Cronbach's α) of .81 and .77. The subscales reflect motivator and hygiene aspects of job satisfaction, and appeared in line with Herzberg's theory. The different types of organizations have the same two-component structure of job satisfaction.

Keywords: Job satisfaction, Scale construction, Categorical principal components analysis, Optimal scaling, Monotonic transformations, Multiple group method.

Introduction

In the social and economic sciences, numerous studies have investigated which worker characteristics and organization features determine or are related to job satisfaction (for an overview see Spector, 1997, pp. 23-54). Starting from psychology, literature about job satisfaction was developed in a wide range of research fields (Locke, 1976). Systematic studies about nature and causes of job satisfaction began in the 1930s, though the importance of the workers' attitudes in determining their satisfaction and productiveness was recognized long before, for example by Taylor in 1912 (Taylor, 1970).

Each study focused on job satisfaction requires a good measurement of this concept, which can be difficult to establish. First of all, there are some problems directly linked to the subjective nature of job satisfaction data. Job satisfaction and, more generally, individual attitudes cannot be observed directly, but are usually obtained from subjective survey questions, for example: "How satisfied are you with your work?". When dealing with such subjective variables, some problems (e.g.,, cognitive dissonance) can arise and affect the meaningfulness of the data (Bertrand & Mullainathan, 2001).

Secondly, the measurement of job satisfaction is complex, because it should take into account the multidimensionality of the concept, in other words, the existence of many aspects composing the concept of interest. Consequently, multiple items are needed to express the different aspects of job satisfaction in a questionnaire (Spector, 1992).

Another problem related to the measurement of subjective attitudes is the necessity to deal with categorical variables. The measuring of individuals' attitudes usually involves the use of questionnaires with several items referring to different aspects of the concept.

Responses indicate the degree of agreement with each statement, with higher scores reflecting a higher degree of agreement. In the survey used for the present study, respondents were asked to answer questions referring to their degree of satisfaction on different items about overall work, intrinsic aspects of work and aspects related to environment. A seven-point response scale was used (1= very dissatisfied, 7 = very satisfied). Consequently, the variables resulting from the questionnaire were ordered categorical (i.e., ordinal) variables. Attention has to be paid to the treatment of ordinal variables, because we cannot assume a priori that the distances between the categories are equal. In analyzing ordinal variables it should be taken into account that the categories of the variable have a fixed a priori order, but this should not be taken to imply that the differences between numeric labels of the categories should be maintained.

A measure of job satisfaction (or any other subjective attitude) can be obtained by constructing multiple items indicating different aspects of the attitude. These multivariate data can be reduced into univariate scales in many ways. Since the beginning of quantitative social sciences, many scholars have studied the dimensionality reduction problem. The univariate scale can be defined by simply adding scores on different variables, as in the case of the *summated rating scale* (Likert, 1932), or by using weighted sums. A well-known technique that allows computing such weights is the linear Principal Components Analysis (PCA). When all the correlations among variables are large, the simple sum is a reasonable choice for a univariate compression of variables (Gifi, 1990; Wainer, 1976). However, PCA is frequently used in data analysis to obtain not just one scale, but a set of subscales, taking into account the multidimensionality of the variables measuring the concept of interest. PCA is used to reduce a number of variables to a much smaller number of principal components, linear combinations of the initial variables, such that they retain as much information as possible. Consequently, instead of the large number of original variables coming from a job satisfaction survey, subscales of the concept can be established and used in other models as dependent or independent variables. Usually, a subscale is the simple sumscore of a subgroup of variables loading high on one particular principal component.

Unfortunately, PCA is based on some assumptions that are often not true in social sciences: all of the variables are assumed to be of numeric (interval or ratio) measurement level and the relationships between variables are assumed to be linear. Because in the social and behavioural sciences many variables are nominal or ordinal and relationships between variables are frequently nonlinear, linear or standard PCA is often not the most appropriate analysis method, although it is commonly used. The standard PCA could be appropriately used in the presence of categorical variables only after verified the existence of linearity in the variables and in the relationships with variables. To avoid the limitations of standard PCA, nonlinear PCA has been introduced and developed during the last 40 years (Gifi, 1990; Linting, Meulman, Groenen, & Van der Kooij, 2006).

Nonlinear PCA, available as the program CATPCA[1] (CATegorical Principal components analysis) implemented in the Categories module of SPSS (Meulman, Heiser, & SPSS, 1999), is an optimal scaling method belonging to the nonlinear multivariate analysis techniques. It is the nonlinear equivalent of PCA: it aims at the same goals of traditional PCA, but it is suited for variables of mixed measurement level that may not be linearly related to each other (Linting et al., 2006). The nonlinear PCA model is the same linear model as in traditional PCA, but it is applied to nonlinearly transformed data. The variables are transformed by assigning optimal scale values to the categories, resulting in numeric-valued transformed variables. So, all the nice mathematical properties of PCA also hold in nonlinear PCA. The nonlinear PCA method is especially suitable for our dimension reduction problem with ordinal variables, because it takes simultaneously into account the nature of items, the different role of items in determining the measure, and the possible multidimensionality of the concept. Moreover in CATPCA, it is implemented in a user-friendly way.

Nonlinear PCA finds category quantifications that are optimal in the sense that the overall variance accounted for in the transformed variables, given the number of components, is maximized. In the optimal scaling process, information in the original categorical data is retained in the optimal quantifications, depending upon the optimal scaling level that can be chosen for each variable separately (see for more details, Meulman, Van der Kooij, & Heiser, 2004; Linting, et al. , 2006). It is important to realize that the distinctions among the different measurement levels of variables (nominal, ordinal, numeric) are based on intrinsic properties of the variables themselves. However, distinctions among the different analysis levels of variables (nominal, ordinal, numeric) depend on decisions of the researcher. The analysis level of a variable, that is, the level on which the researcher chooses the variable to be analyzed, and the measurement level need not be equal (Gifi, 1990). In this paper, we will refer to the analysis level as the *scaling level*. Unlike the original labels of the nominal or ordinal variables in the analysis, the transformed variables have metric properties. This allows one to use all standard methods conceived for dealing with continuous variables.

Nonlinear transformations can be nonmonotonic and monotonic. Usually, monotonic transformations are suited for ordered categorical or continuous data, while nonmonotonic functions are used to transform nominal data. Actually, nonmonotonic transformations can also be used for numeric and ordinal variables when nonlinear relationships among variables are assumed (Meulman et al., 2004, p. 50).

The aims of the present study are to identify the component structure of job satisfaction measured by items with a Likert-type response scale, and to summarize the data contained in numerous items into one ore more subscales of job satisfaction that can be used in further models. We will investigate whether the component structure found by categorical principal components analysis is stable using a number of random samples drawn from the data, is consistent within different types of organizations, and can be confirmed using the multiple group method (MGM; Holzinger, 1944; Nunnaly, 1978) on a test sample randomly drawn from the data.

Organizational Context

Our dataset was collected in a survey[2] described by Borzaga (2000) and coordinated by ISSAN (Istituto Studi Sviluppo Aziende Nonprofit) of University of Trento. ISSAN is an institute of the University of Trento that is interested in studies about development of nonprofit companies. The organizations under study were providers of social services operating in 15 Italian provinces[3] The Italian social service sector is, as a whole, very heterogeneous with regard to the services supplied, final users and organizational forms. Social services included health services, support, services of career guidance and school orientation, and services of settling in work. These services were provided for old people, for handicapped, for mental patients, for minors or young people, for workers, and for unemployed people. With regard to the organizational forms, five different legal types can be distinguished in the considered organizations: social cooperatives, public bodies, for profit, lay non-profit and religious non-profit organizations.

The survey is the first national survey about the social service sector realized in Italy and it had at least two main aims. Firstly, it aimed to identify how the social service sector works. The social service sector is a peculiar sector with its own distinctive rules. For example, because the monetary aspects do not predominate as in other sectors, other aspects, such as motivation and satisfaction, are needed to explain why a lot of people spend their time working, sometimes without being paid (i.e., as voluntary workers). Secondly, the survey wanted to identify differences in job satisfaction, among other matters, within different types of organizations.

Method

Sample

A sample of organizations was drawn from the 15 provinces. In each province two or three different kinds of social services were analyzed, chosen from the most common types in each region. The sampling was done in the following way. First, all the organizations were listed in each province. The organizations sampled from these lists had to satisfy the following conditions: (a) at least three years of existence (from 1 January 1994); (b) consecutive supply of services; and (c) minimally three paid workers per supply unit. If the organization contained more than one supply unit, only one unit was considered if this unit included at least ten paid workers and ten voluntary workers. Otherwise, several supply units were considered but not more than three. Finally, a sample of 228 organizations (and 268 supply units) was obtained.

The workers sample consisted of the manager of each supply unit of each organization and a sample of 20 staff members, obtained in the following way. If the staff consisted of less than 20 people, then the entire staff was included in the sample; if the staff consisted of more than 20 people, a sample of ten paid workers and ten voluntary workers was selected, if possible. Otherwise, all workers in the category with fewer than ten people were selected and, from the other category, a number of workers was selected such that the total sample size was 20. Samples were selected in order to be representative with regard to professional area, position, and sex. In order to keep a representative sample, in some organizations a sample of more than 20 workers was selected with a maximum of 42. The final sample included 2066 paid workers, 724 voluntary workers and 266 managers.

We used the subsample of paid workers, drawn from 220 organizations. Twenty-seven workers had missing values on all job satisfaction variables. The final data set used for the analysis contained 2039 workers. This resulted in data being collected from 70 social cooperatives (SC) (560 workers), 52 public bodies (PB) (563 workers), 16 for profit (FP) (174 workers), 42 lay non-profit (LNP) (398 workers) and 27 religious non-profit (RNP) (234 workers). For 13 organizations (110 workers) the type of organization is missing.

Questionnaires

Two different questionnaires were used: one for the organizations, and one for the paid workers. The organization questionnaire was filled in during a face-to-face interview with managers of the organization. Workers filled in the questionnaire at their work place and in presence of the survey staff, who were only permitted to give some explanation of questions.

From the organization questionnaire, we only used the variable type of organization (Type), which has the five categories (see end of the previous section). The questionnaire for workers consisted of two parts. The first part referred to personal and professional information. The second part referred to work-related attitudes, to job satisfaction, to relationships with end users, and to relationships with colleagues and superiors. We used the section from the second part referring to satisfaction, consisting of 15 items. One item measured satisfaction about the overall work, and 14 items measured satisfaction about a variety of aspects of the work: formative training and professional growth (Growth), decisional and operative independence (Indep), recognition by the others for work done (Recog), variety and creativity of work (Variety), physical environment of work (Physical), benefit that his/her work produces for end users (Benefit), wage (Wage), working hours (Hours), career promotions achieved until this moment in this organization (Carprom), career prospects (Carprosp), certainty of job (Certainty), relationship with superiors (Superiors), relationship with paid colleagues (Colleagues), and relationship with voluntary workers (Voluntary). In an initial analysis, we investigated whether to include the variable Voluntary. This item was relevant only for a subset of 784 workers who were in contact with voluntary workers. We performed two principal component analyses on this subset, one including the variable Voluntary and one excluding it. The results were very similar; the correlations of the component scores were .996 (first component) and .928 (second component). So, we decided to exclude the variable Voluntary, leaving 13 variables for the main analyses.

Data analysis

We computed the percentage of missing values for each of the 13 variables. For all variables this was less than 10%. Missing values on a variable were imputed with the corresponding mode. To examine the component structure of the 13 ordinal variables we applied CATPCA to a random sample (0.75*N*) from the data. We refer to this subset as the training set. The remaining subset (0.25*N*) will be used as test set. Comparisons of the solutions for the training set obtained with different scaling levels were based on the Total Percentage of Variance-Accounted-For (Total PVAF) in the transformed variables, on Cronbach's α (Cronbach, 1951) and on the transformation plots, where the category quantifications are plotted against the original category labels.

In order to study the stability of the solution found for the training set, another nine subsets of size 0.75*N* were randomly drawn from the total sample. We assessed the stability of the CATPCA solutions for the ten subsets (including the training set) with regard to (a) Total PVAF and Cronbach's α, (b) the loadings and (c) the category quantifications in order to assess the appropriateness of the choice of the optimal scaling level, of the number of dimensions, and of the component structure of job satisfaction. If necessary, some instability can be reduced by merging an unstable category with an adjacent category, or by discarding variables causing instability. If this is the case, the stability study should be repeated on the ten previously extracted random samples, after having merged categories or excluded variables.

In addition, we investigated whether the five different types of organizations reflect the same structure of job satisfaction. With CATPCA, a grouping variable can be fitted in the solution by choosing a “multiple nominal” scaling level and treating the variable as supplementary (the variable is not included in the analysis, but is fitted in the solution for the analysis variables). With a multiple nominal scaling level, unlike with the other scaling levels, a variable does not obtain *one* set of quantifications but *multiple* sets of quantifications, a different set for each component. In graphical terms, a variable with multiple nominal scaling level is represented by category points, while a variable with one of the other scaling levels is represented by a vector. A category point is the centroid of the object scores of the persons that scored the category, that is in our case, the persons that belong to a specific type of organization. The joint plot of category points and vectors can be inspected to see the location of the category points in relation to the other variables. If the types of organization are different with respect to the aspects measured by the other variables, this is reflected in a considerable spread of the category points. Thus, if the category points are all relatively close to the origin, the types of organizations are not different with respect to their patterns on the other variables.

Confirmatory principal components analysis using the multiple group method (MGM; Holzinger, 1944) was applied to investigate whether the structure found by CATPCA was confirmed in the test sample (of size 0.25*N*). The aim of MGM is to test whether or not an a priori idea about the assignment of items to subscales is supported by the data. (In our study, that is deduced form the CATPCA solution). The method consists of (a) constructing the subscales as simple sums of the items assigned to that particular subscale; (b) computing the item-rest correlations within each subscale (i.e., the correlation between an item and the sum of all items belonging to the subscale, except for the considered item). To correct for the subscale length (i.e., the number of assigned items) the formula suggested in Guilford (1954, p. 407) was used. Although other methods of confirmatory analysis (for example, the confirmatory common factor approach, Jöreskog, 1966, 1969) are theoretically more elegant, the MGM is very simple to understand to a broader audience and it has been shown to perform well and to provide clear conclusions about the goodness of the assignment of items to a subscale (Stuive, Kiers, Timmerman & Ten Berge, 2006) . The subscales of job satisfaction are computed as the sum of the transformed variables with high rotated loadings on a specific principal component. The reliability (Cronbach's α) of the scores of these subscales was assessed, and the Pearson correlation coefficient between subscales was computed.

Results

On the training set, we performed four CATPCA analyses with two components[4] with different scaling levels: nominal, ordinal, spline ordinal (second degree monotonic splines with two interior knots; see Ramsay, 1988), and numeric. Table 1 shows the fit indices for each scaling level. In terms of PVAF and Cronbach's α, the nominal, ordinal, and spline ordinal solutions are very similar. The PVAF of the numeric solution is about 2% lower than the others. The similarity between the nominal and (spline) ordinal solutions is also reflected in the transformation plots (see appendix A for the plots of the nominal solution and appendix B for the plots of the spline ordinal solution). The transformations for the nominal level show, in most cases, an increasing trend. This means that there is a natural order in the categories of the observed variables, as expected, as all of them measure the level of satisfaction. In such a situation (spline) ordinal transformations give similar fit (Meulman *et al*., 1999). Because we preferred the more parsimonious (more restrictive) transformations, we chose the spline ordinal scaling level. The numeric level is even more parsimonious, but would be too restrictive to reveal the nonlinearities in some of the variables. Looking at the transformation plots for the spline ordinal scaling level in more detail, we see that some variables obtained transformations close to linear (meaning that the categories of these variables are ordered and almost equally spaced); these variables are: Growth, Indep, Recog and Variety. The transformation of other variables was more nonlinear. The variables Physical, Benefit, Wage, Hours, Certainty, Superiors, and Colleagues showed a transformation that approximates a convex function, indicating that there was less distinction between the categories of lowest levels of satisfaction and more contrast between categories of the highest levels of satisfaction. For variables Carprom and Carprosp the transformation was also nonlinear but showed concavity: there was less distinction between the higher levels of satisfaction categories than between the lower ones.

The next step of our analyses was to determine the number of components. For this, we used the “eigenvalue greater than one” criterion (eigenvalues represent variance-accounted-for (VAF), so a component with an eigenvalue less than one explains less variance than an individual standardized variable) and the Scree test (Cattell, 1966). In an initial CATPCA for the training set with the maximum number (13) of components the first three eigenvalues were greater than one (the values of the first four eigenvalues were 4.736, 1.386, 1.165, and 0.892). Then, we performed a CATPCA with three components to check the sizes of the eigenvalues of the correlation matrix of the transformed variables of this solution. We performed this check because CATPCA solutions are not nested (except when the numeric scaling level is chosen for all variables), that is, the first three components of the 13-component solution are not equal to the three components of the 3-component solution. As an illustration, the total PVAF of the first three components of the 13-component solution was 55.99, while the total PVAF of the 3-component solution was 57.38. CATPCA solutions with numeric scaling level for all variables (which is equivalent to linear PCA) are nested, because the correlations between the variables are fixed. In CATPCA, these correlations are not fixed but depend on the transformations. The transformations can be (sometimes slightly) different for solutions with different numbers of components because CATPCA maximizes the first p eigenvalues of the correlation matrix of the transformed variables, with p being the number of components.

The scree plot shows how the VAF of the components decreases. What we look for in a scree plot is an “elbow”: the location where the decrease in size of the eigenvalues starts to level off. In Figure 1, we see that the scree plot suggests two or three components. Because the two criteria we used were not decisive (three or two), we used a third criterion: the interpretability of the components.

To interpret the components we inspected the component loadings. The current version of the CATPCA program does not offer rotation options. Unrotated solutions can sometimes be difficult to interpret, as was the case in our study. Therefore, we used the transformed variables as input for a classical PCA (the unrotated result of this is identical to the CATPCA solution), with *varimax* rotation (Kaiser, 1958). The rotated components remain uncorrelated with this type of rotation. We inspected the rotated 3-component solution (Table 2) and the rotated 2-component solution (Table 3). We will assign variables only to one subscale, to facilitate the interpretation of the subscales and to decrease intercorrelation of the subscales; if a variable had a relatively high loading (> .40) on both components, we chose the highest loading. The first component of the 3-component solution included variables related with the work itself: Growth, Indep, Recog, Variety, and Benefit. The second component included variables related to the environment in which people work: Physical, Wage, Hours, Certainty, Superiors, and Colleagues. The third component included only two variables, Carprom and Carprosp.

The 2-component solution (Table 3) only differed from the 3-component solution with regard to the variables Benefit, Carprom and Carprosp. Note that the second component in Table 2 is the same as the first component in Table 3, except for Benefit. In accordance with the solution in Table 3, we could consider two subscales: the first one including aspects related to the environment of work, and the second one including all intrinsic aspects of work (see numbers in bold face in Table 3). The interpretation of Benefit appears to be ambiguous. It refers to the level of satisfaction with the benefit that the work produces for end users. It can be interpreted as an intrinsic aspect of work, but also as an extrinsic one, because it involves the others' opinion.

Although the component loadings of Carprom and Carprosp on the third component in the rotated solution were high (.861 and .858 respectively, see Table 2), two variables with high loadings are, in general, too few to form a separate component. Stevens (1992) suggested that reliable components should have a minimum of four loadings above .60. Furthermore, the decrease in total percentage of VAF from the 3-component to 2-component solution was rather small (8.383%). In addition, the loadings of Carprom and Carprosp were also high on the second component of the 2-component solution (.844 and .848 respectively, see Table 3), indicating they also fitted well in the 2-component solution. Therefore, we decided to use the 2-component solution.

The stability of the above-mentioned CATPCA results was studied using ten random samples of size 0.75*N* (including the training set). The solution with spline ordinal was always preferable (with regard to the goodness-of-fit indices) than the solutions with other scaling levels in the 2-component solution. The number of components in the 13-component solution that have an eigenvalue greater than 1 is three in every random sample, and in the 3-component solution Carprom and Carprosp are the only variables loading high on the 3rd dimension of the rotated solution in each random sample. Figure 2.a shows the loadings of the 13 satisfaction variables in the rotated 2-component solution obtained for each random sample. We inspected the position of the variable loadings in relation to the reference line. The reference line indicates the position of variables with equal loadings on both components. Thus, if a variable is above the reference line, it means that the loading of that variable is smaller on the first component than on the second component. This implies that the variable will be assigned to the second subscale. If the solution is stable, the spread of the ten component loadings on the first and on the second dimension of each variable is small. A stable component structure is obtained if the 10 points of the same variable are all above or below the reference line; in that case, we always assign the variable to the same subscale. Figure 2a shows a large spread around the reference line. As a consequence, the assignment of some variables to the subscales will vary in the ten samples (e.g., the variable Wage).

The instability in the component structure was most probably due to the high correlation (r = .74) between the variables Carprom and Carprosp. Their intercorrelation was much higher than the intercorrelation of the other variables (varying between .09 and .52). Both variables measure the same aspect of job satisfaction, that is, satisfaction with career. Together, they form a unique subscale of satisfaction in the 3-component solution of every random sample. Therefore, we discarded one of the two variables (Carprosp, with higher number of missing values) and repeated the analysis on the ten previously extracted random samples. The exclusion of Carprosp decreased the spread in the position of the variables in relation to the reference line, which is displayed in Fugure 2b. This figure shows a more identifiable structure of job satisfaction: the items are always assigned to the same subscale. None of the variables shows moderately high correlations on both scales anymore.

Figure 3 shows the least stable variables with regard to their category quantifications. The difference between the highest and lowest quantification was about 1 or smaller (the highest differences, 1.06 and 1.12, were found for category 1 and 2 of the variable Benefit). The final component structure was obtained by the rotated 2-component CATPCA solution (with spline ordinal scaling level) without Carprosp. The PVAF of this solution in the training set was 48.52 (24.62 by the first rotated component, and 23.90 by the second one). Table 4 shows the corresponding loadings.

With reference to the structure of job satisfaction in the five different types of organizations, the CATPCA plot of loadings and category points (Figure 4) showed that the five group points lay relatively close together around the origin, which indicates that the component structure was not notably different among the groups. As quantified variables are standardized variables, the differences in the category quantifications of the types of organizations (for each component) are small. Thus, we concluded that the 2-component structure of job satisfaction found by CATPCA holds in the five different types of organizations.

The confirmatory principal components analysis (with the MGM method) was applied to the test set. In a first step, we replaced the original category labels in the test set with the quantifications found for the training set. Then, two subscales were created by summing the values of the transformed variables with a high component loading in the training set on that particular component (that is, the loadings displayed in bold in Table 4). Instead of using the original variables, we preferred to use the transformed variables to take into account the (sometimes slight) nonlinearity of most transformations. Because of the similarity of the component loadings (in sign and size) in our case, there is not much difference between a weighted sum and an unweighted sum (in the test set, the correlation between the weighted and the unweighted subscales is almost one for both subscales). Therefore, we decided to use simple summation, that is, we reduced the loadings to binary weights [1,0]. The results of the MGM analyses (see Table 5) confirm the component structure of job satisfaction identified by CATPCA: The (item-rest) correlation of an item with the subscale it was assigned to was always higher than the (item-total) correlation with the subscale it was not assigned to. Correction of the correlations for test length gave similar conclusions (see Table 5). The two subscales, constructed by simple summation, explain 46.82% of the variance in the transformed variables in the test set, which is only 1.70% lower than the total PVAF of the CATPCA solution with optimal weights obtained in the training set.

The final step of the analyses involved examining the reliabilities of the scores of the two subscales. The reliability analysis applied to the transformed variables showed no need to delete an item: α = .774 in the training set and .748 in the test set for the first subscale, and α = .790 in the training set and .786 in the test set for the second subscale. The correlation between the two final subscales was .533 in the training set and .493 in the test set.

Discussion

The aim of this study was to identify the component structure of job satisfaction in the Italian social service sector by analyzing survey-data using nonlinear principal components analysis (nonlinear PCA): starting from a set of items drawn from a questionnaire, we wanted to see whether the construct of job satisfaction consists of one or more sets of components and how these components are composed. The final objective was summarizing the data contained in numerous items to obtain a measure of job satisfaction that can be used in further models.

To establish the component structure, we used nonlinear PCA (with the program CATPCA). The main advantages of this approach compared to classical PCA are that (a) it takes into account the categorical (in this case ordinal) nature of variables under study; (b) it does not rely on normality and linearity assumptions; and (c) it enabled us to examine the behavior of multiple groups in the same analysis in order to see whether they differed with respect to the component structure. Because CATPCA is an explorative technique, there is a risk of fitting structures that are very sample-specific. Therefore, it is important to conduct a stability study. We found a stable CATPCA solution by excluding one variable (Carprosp), which caused instability of the component structure.

This study underlines the importance of the measuring of job satisfaction also in the social service sector. In particular, an important implication for career counseling concerns the inclusion of the career variables in a job satisfaction scale. In the questionnaire used in this study the variables Carprom and Carprosp were included. They measure two different aspects: the “past” career (Carprom: career promotions achieved until this moment in this organization) and the “future” career (Carprosp: career prospects). As already noted, their intercorrelation was much higher than the intercorrelation of the other variables. This was because both variables measure satisfaction with career and , particularly in the Italian social service sector, most of the workers have a fixed-term or short-term position. It is difficult for those workers to evaluate their satisfaction with career and to distinguish past from future career. We discarderd Carprosp from the analyses and we suggest to merge the two items into one single item in the questionnaires aimed at evaluating the job satisfaction in all those sector having many workers without long-term positions.

Why did we not use factor analysis? In the literature, the decision to use PCA or factor analysis (FA) is a much-discussed question and comparisons between the two techniques are the object of many contributions (a.o., Thompson, 2004, Fabrigar, Wegener, MacCallum, Strahan, 1999, Mulaik, 1992). Some authors consider PCA as a method of FA

(Thompson, 2004); whilst other scholars think that they are conceptually very different (Fabrigar et al., 1999). The two methods are based on different philosophies: The goal of PCA is to extract maximum variance from a data set with a few components, while the goal of FA is to reproduce the correlation matrix with a few factors (Tabachnick & Fidell, 1989). If one is interested in a theoretical solution and want to take into account unique and error variability, FA is the right choice. PCA is more appropriate when the objective is to get an empirical summary of the data set (Tabachnick & Fidell, 1989). It is important to note that, when the number of measured variables is large -also with respect to the supposed number of latent variables (as is the case in our study)- PCA and FA lead to the same results (Thompson, 2004; Fabrigar et al., 1999).

A possible limitation of the present study is the way the missing values were imputed, namely with the variable mode. The percentage of missing values in our dataset was relatively small, that is, lower than 10%. We compared the results of mode imputation method with a more advanced strategy of missing values in CATPCA, namely passive treatment. In this strategy, the missing values are not imputed but ignored, that is, only the entries in the data that contain valid values are used in the analysis. Thus all participants are in the analysis, but only for the variables on which they have valid values. This strategy is something different than pairwise deletion; with passive handling of missing values nothing is deleted (and nothing is imputed); this strategy is possible in CATPCA because finding the CATPCA solution, unlike the traditional PCA solution, does not involve the correlation matrix. As a result, the transformed (quantified) dataset has missing values where the original dataset has missing values. By contrast, the mode imputation strategy results in a transformed dataset without missing values. We checked the correlations between the component scores obtained using the mode imputation strategy and the passive treatment of missing values. The correlation coefficients were relatively high (.985 for the first component and .880 for the second component), suggesting that the mode imputation did not affect the solution much. Because we preferred a transformed dataset without missing values for further analyses, we used the mode imputation strategy.

The obtained two subscales of job satisfaction can be interpreted in the light of the well-known Herzberg's Two-Factor theory, also called Motivation-Hygiene theory (Herzberg, Mausner, & Snyderman, 1959). In his theory, Herzberg suggested that job satisfaction and job dissatisfaction are caused by different and independent sets of factors. Job satisfaction is caused, on the one hand, by a set of factors related to the work itself, such as nature of job, achievement in the work, possibilities of personal growth and recognition, and promotion opportunities. These factors are called *motivators* by Herzberg, as they should motivate people to higher performances. Our subscale composed of variables Growth, Indep, Recog, Variety, and Carprom can be considered as the subscale of motivators. On the other hand, job *dis*satisfaction is a result of the so-called *hygiene* (or *maintenance*) factors, which are "conditions that surround the doing of the job" (Herzberg, 1966, p. 113), such as (physical) working conditions, salary, company policies, job security, quality of supervision, and relations with others. These factors are not an intrinsic part of a job but they refer to the environment and have the function of preventing job dissatisfaction. Our subscale composed of variables Physical, Benefit, Wage, Hours, Certainty, Superiors, and Colleagues refers to the so-called hygiene factors. The results of our study confirm Herzberg's theoretical two factors of Motivation and Hygiene, but not their independence (the correlation between the two final subscales is .533 in the training set and .493 in the test set).

A systematic review concerning the reliability and validity of some existing instruments measuring job satisfaction can be found in Van Saane, Sluiter, Verbeek and Frings-Dresen, 2003. Unlike some of those instruments, such as the Emergency Physician Job Satisfaction Scale (Lloyd, Streiner, Hahn, & Shannon, 1994), that are designed for specific jobs, our subscales were designed for a broader range of occupations. Furthermore, our subscales cover most of the standard work aspects represented by other multidimensional instruments (e.g., the Job Satisfaction Survey [Spector, 1985]).

In a next study, the relationship of the job satisfaction subscales obtained in the present study with other aspects of quality of work (fairness, motivation to work, and effort) will be investigated. While writing this paper, a new, broader survey investigates the characteristics of the social service sector in Italy. The questionnaire including the job satisfaction items was adapted according to the present results.

Notes

[1]CATPCA was formerly known as PRINCALS, which is included in the earlier versions of SPSS Categories.

[2]The survey was sponsored by FIVOL “Fondazione Italiana per il VOLontariato” (Italian Foundation of Voluntary work) and by FEO “Fondazione Europa Occupazione” (Europe Employment Foundation), both in Rome.

[3]The 15 provinces involved in the survey were: Torino, Cuneo, Brescia, Trento, Venezia, Udine, Pordenone, Gorizia, Trieste, Firenze, Salerno, Napoli, Catanzaro, Reggio Calabria, Messina.

[4]The number of components is in line with previous work (Carpita, 2003).

References

Borzaga, C. (2000). *Capitale umano e qualità del lavoro nei servizi sociali* [Human capital and job quality in social services]. Roma, Italy: FIVOL.

Carpita, M. (2003). Metodi per la costruzione di indicatori della qualità del lavoro: Un’applicazione al settore dei servizi sociali (comment: insert the title translation?). *Statistica & Applicazioni*, *1*, 3-33.

Cattell, R. B. (1966). The Scree Test for the Number of Factors. *Multivariate Behavioral Research, 1,* 245-276.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16,* 297-334.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*, 272-299.

Gifi, A. (1990). *Nonlinear multivariate analysis*. Edited by Heiser W., Meulman J. J., & van den Berg, G., Wiley, Chichester.

Guilford, J. P. (1954). *Psychometric methods* (2nd ed.). New York: McGraw-Hill.

Herzberg, F., Mausner, B., & Snyderman, B. B. (1959). *The motivation to work*. New York: John Wiley and sons.

Herzberg, F. (1966). *Work and the nature of man*. Cleveland, Ohio: World Publishers.

Holzinger, K. J. (1944). A Simple Method of Factor Analysis. *Psychometrika*, *9*, 257-261.

Jöreskog, K. J. (1966). Testing a simple structure hypothesis in factor analysis. *Psychometrika*, *31*, 165-178.

Jöreskog, K. J. (1969). A general approach to confirmatory maximum liklihood factor analysis. *Psychometrika*, *34*, 183-202.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, *23*, 187-200.

Kreitner, R., Kinicki, A., & Buelens, M. (1999). *Organizational behaviour*. London: McGraw-Hill.

Likert R. (1932). “A technique for the measurement of attitudes”. *Archives of psychology*, 22, No. 140.

Linting, M., Meulman, J. J., Groenen, P. J. F., & Van der Kooij, A. J. (2006). *Nonlinear principal components analysis: Introduction and application*. Manuscript submitted for publication.

Lloyd, S., Streiner, D., Hahn, E., & Shannon, S. (1994). Development of the emergency physician job satisfaction measurement instrument. *American Journal of Emergency Medicine*, *12*, 1-10.

Locke, E. A. (1976). The nature and causes of job satisfaction. In M. D. Dunnette (Ed.), *Handbook of industrial and organizational psychology* (pp. 1297-1349). Chicago: Rand McNally College Publishing Company.

Meulman, J. J., Heiser, W. J., & SPSS (1999). *SPSS Categories 10.0*. Chicago: SPSS Inc.

Meulman, J. J., Van der Kooij, A. J., & Heiser, W. J. (2004). Principal components analysis with nonlinear optimal scaling transformations for ordinal and nominal data. In D. Kaplan (Ed.) *Handbook of quantitative methodology for the social sciences* (pp. 49-70). London: Sage.

Mueller, C. W., & McCloskey, J. C. (1990). Nurses' job satisfaction: a proposed measure. *Nursing Reasearch, 39,* 113-117.

Mulaik, S. A. (1992). Guttman's "Last Paper": A Commentary and Discussion Editor's Introduction. *Multivariate Behavioral Research, 27*, 173-174

Nunnaly, J. (1978). *Psychometric theory*. New York: McGraw-Hill.

Podsakoff, P. M., & Williams, L. F. (1986). The relationship between job performance and job satisfaction. In E. A. Locke (Ed.). *Generalizing from laboratory to field settings: research findings from industrial-organizational psychology, organizational behaviour, and human resource management* (pp. 207-254). Lexington: Lexington Books, D. C. Health and Company.

Ramsay, J. O. (1988). Monotone regression splines in action. *Statistical Science, 3*, 425-441.

Spector, P. E. (1985). Measurement of human service staff satisfaction: development of the Job Satisfaction Survey. *American Journal of Community Psychology, 13,* 693-713.

Spector, P. E. (1992). *Summated rating scale construction, an introduction*. London: Sage Publications.

Spector, P. E. (1997). *Job Satisfaction. Application, assessment, causes, and consequences*. Thousand Oaks, California: Sage Publications, Inc.

Stevens, J. (1992). *Applied multivariate statistics for the social sciences (2nd ed.)*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Stuive, I., Kiers, H. A. L., Timmerman, M. E., & Ten Berge, J. (2006). *A comparison of methods for the empirical verification of an assignment of items to subtests: Oblique Multiple Group Method versus Confirmatory Common Factor Analysis*. Manuscript submitted for publication.

Tabachnick, B., & Fidell, L. (1989). *Using Multivariate Statistics*. New York: Harper & Row Publishers.

Taylor, F. W. (1970). *What is scientific management*? In H. F. Merril (Ed.). *Classics in management* (pp. 67-71). (Rev. Ed.) New York: American Management Association.

Thompson, B. (2004). Exploratory and confirmatory factor analysis: Understanding concepts and applications. Washington, DC: American Psychological Association.

Ullman, J. B., & Bentler, P. M. (2003). Structural equation modeling. In I. B. Weiner, J. A. Schinka, & W. F. Velicer (Eds.), *Handbook of psychology*, vol.2: Research methods in Psychology (pp. 607-634). Hoboken, NJ: Wiley.

Van Saane, N., Sluiter, J. K., Verbeek, J. H. A. M., & Frings-Dresen, M. H. W. (2003). Reliability and validity of instruments measuring job satisfaction – a systematic review. *Occupational Medicine, 53,* 191-200.

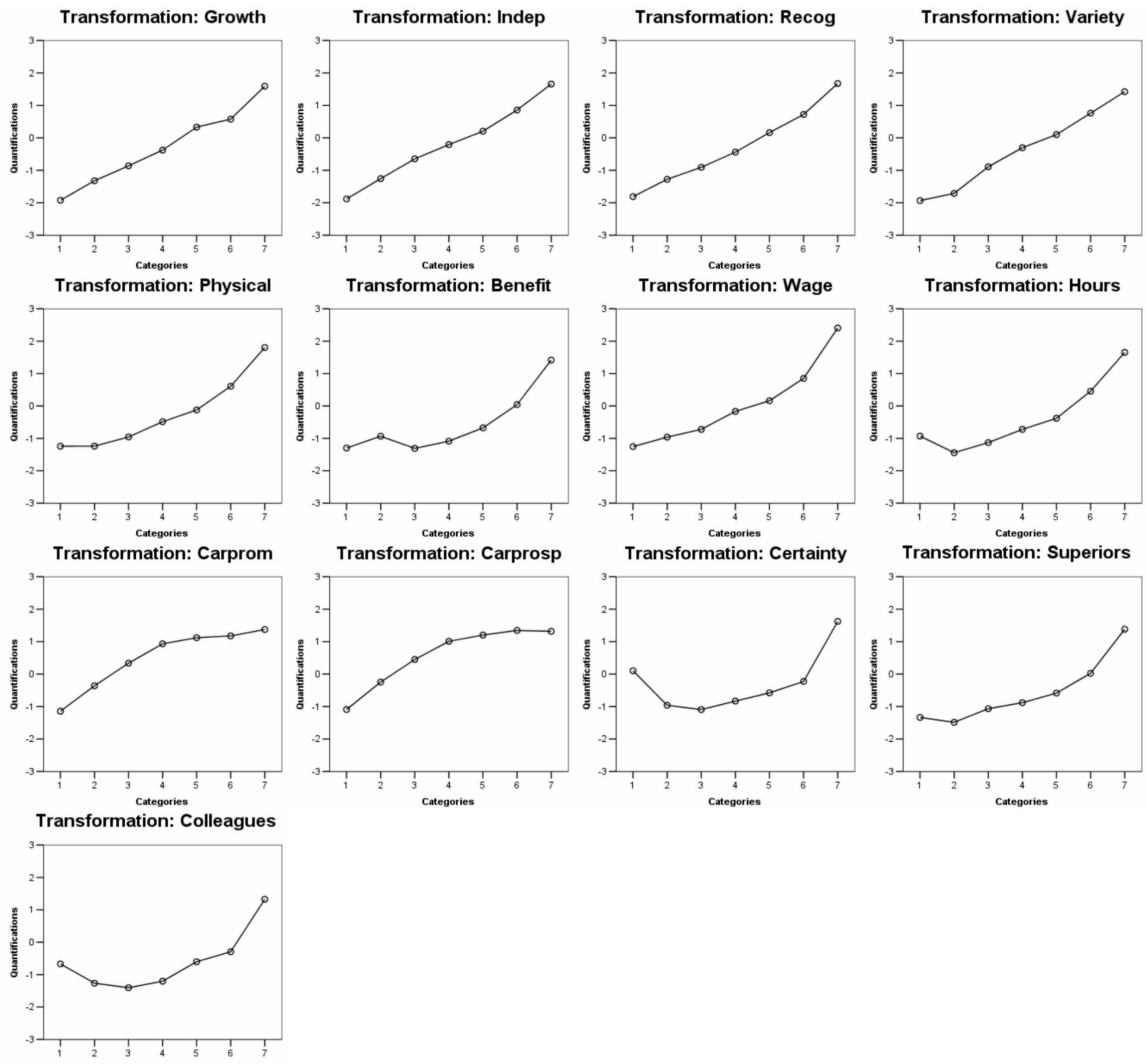
Wainer, H. (1976). Estimating coefficients in linear models: it don't make no nevermind. *Psychological Bulletin, 83,* 213-217.

Whitsett, D. A., & Winslow, E. K. (1967). An analysis of studies critical of the motivator-hygiene theory. *Personnel Psychology, 20,* 391-415.

Appendix A

Transformation Plots of the 13 Items of Job Satisfaction Treated at a Nominal

Scaling Level in Categorical Principal components analysis



Appendix B

Transformation Plots of the 13 Items of Job Satisfaction Treated at a Spline Ordinal Scaling Level in Categorical Principal components analysis

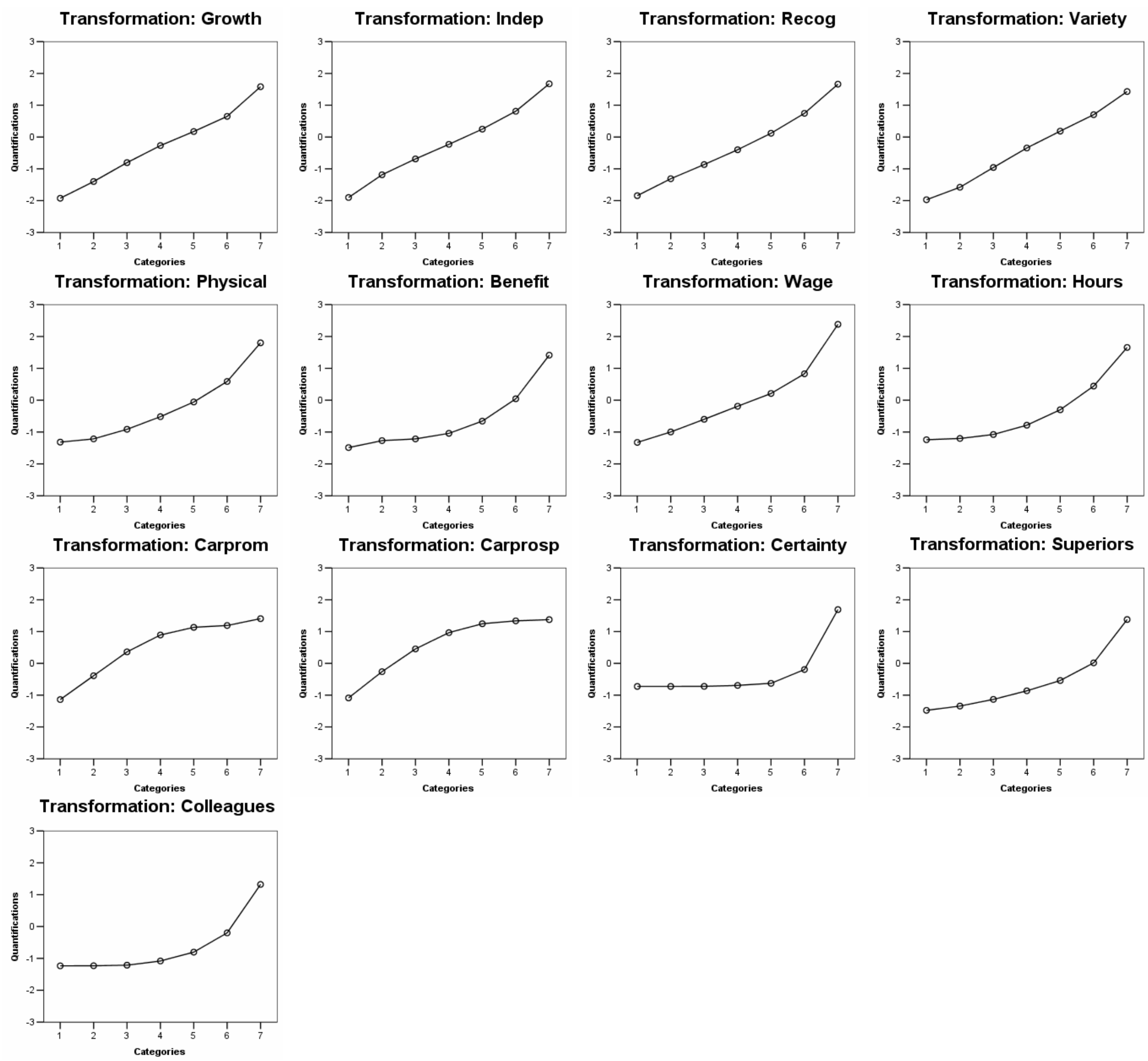


Table 1. Percentage of Variance-Accounted-For (PVAF) and VAF (Eigenvalue) obtained by CATPCA with two components selecting nominal, ordinal, spline ordinal, and scaling levels applied to the training set

	Nominal	Ordinal	Spline Ordinal	Numeric
PVAF Total	49.284	49.105	49.001	47.242
VAF Total	6.407	6.384	6.370	6.141
PVAF 1st component	34.904	35.327	35.223	36.664
VAF 1st component	4.538	4.593	4.579	4.766
PVAF 2nd component	14.380	13.777	13.778	10.578
VAF 2nd component	1.869	1.791	1.791	1.375
Cronbach's α	0.914	0.914	0.913	0.907

Table 2. Rotated component loadings of the 3-component CATPCA solution for the training set[a]

	Component		
	1	2	3
Growth	**.673**	.159	.303
Indep	**.710**	.169	.279
Recog	**.692**	.238	.178
Variety	**.734**	.075	.183
Physical	.280	**.623**	.185
Benefit	**.534**	.330	-.269
Wage	.042	**.621**	.387
Hours	.1851	**.682**	.073
Carprom	.225	.091	**.861**
Carprosp	.239	.069	**.858**
Certainty	.022	**.720**	-.039
Superiors	.453	**.587**	.057
Colleagues	.386	**.534**	-.134

[a]The strongest correlation of a variable to a component appears in bold.

Table 3. Rotated component loadings of the 2-component CATPCA solution for the training set[b]

	Component	
	1	2
Growth	.353	**.615**
Indep	.382	**.620**
Recog	.468	**.521**
Variety	.350	**.543**
Physical	**.592**	.315
Benefit	**.609**	.016
Wage	**.434**	.353
Hours	**.629**	.169
Carprom	-.098	**.844**
Carprosp	-.112	**.848**
Certainty	**.644**	-.056
Superiors	**.686**	.287
Colleagues	**.660**	.097

[b]The strongest correlation of a variable to a component appears in bold.

Table 4. Rotated component loadings of the 2-component CATPCA solution (without Carprosp) for the training set[c]

	Component	
	1	2
Growth	.215	**.733**
Indep	.219	**.764**
Recog	.328	**.655**
Variety	.153	**.723**
Physical	**.606**	.315
Benefit	**.502**	.210
Wage	**.513**	.270
Hours	**.657**	.175
Carprom	.074	**.650**
Certainty	**.713**	-.063
Superiors	**.679**	.320
Colleagues	**.663**	.132

[c]The strongest correlation of a variable to a component appears in bold.

Table 5. Correlations between the transformed variables and the two subscales of job satisfaction in the test set[d]

			Correlations corrected for subscale lenght	
	Subscale 1	Subscale 2	Subscale 1	Subscale 2
Growth	.341	.579	.215	.425
Indep	.357	.651	.225	.478
Recog	.487	.616	.307	.452
Variety	.337	.535	.213	.393
Physical	.524	.377	.331	.277
Benefit	.327	.160	.206	.117
Wage	.468	.400	.295	.294
Hours	.512	.369	.323	.271
Carprom	.286	.435	.180	.319
Certainty	.411	.141	.259	.103
Superiors	.587	.487	.370	.357
Colleagues	.422	.246	.266	.181

[d]The table shows the item-rest correlation if an item belongs to a subscale and the item-total correlation otherwise.

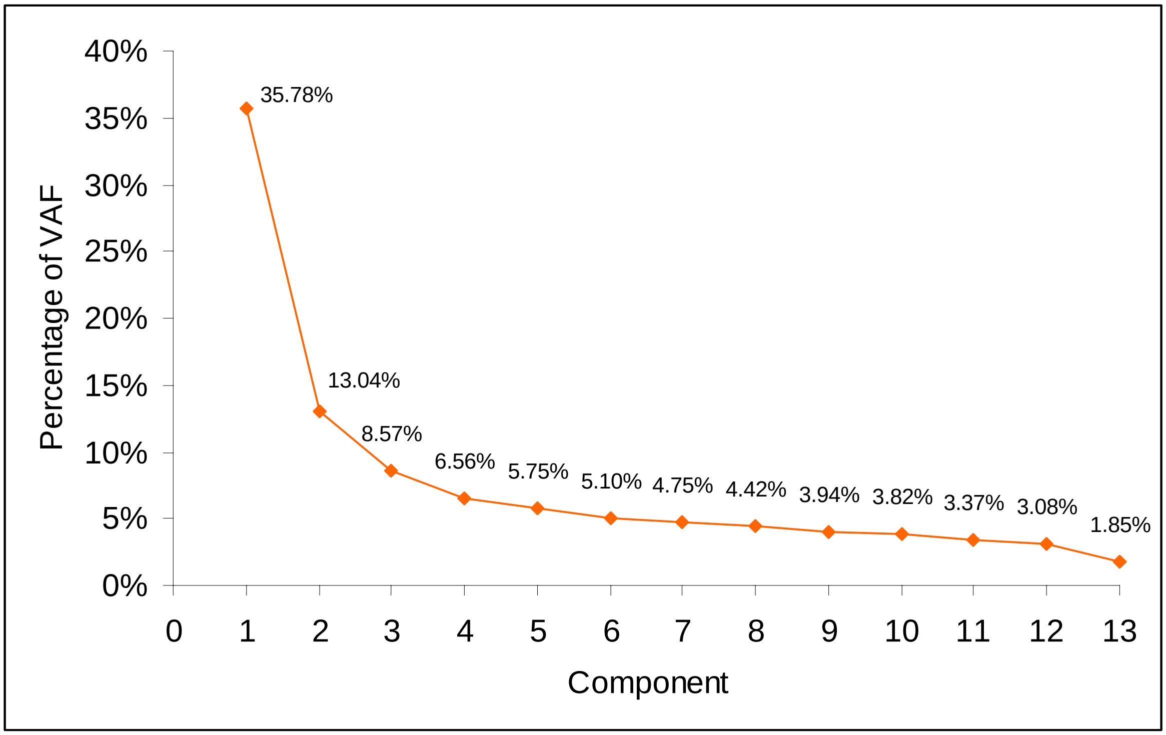
Figure Captions

Figure 1. Screeplot of the 3-component CATPCA solution.

Figure 2. Loadings of the 13 satisfaction variables in the rotated 2-component CATPCA solution obtained with 10 random samples (0.75*N*) (*a*) before and (*b*) after excluding variable Carprosp. The position of a variable in relation to the line indicates the component to which the variable is assigned (below the line first component, above the line second component).

Figure 3. Transformation plots of the variables Physical, Benefit and Carprom obtained with 10 random samples (0.75*N*) after excluding variable Carprosp.

Figure 4. Loadings of the 13 satisfaction variables (vectors) and five category points representing the five types of organization: SC = social cooperatives; FP = for profit; PB = public bodies; LNP = lay non profit; RNP = religious non profit.


40%
35%
30%
25%
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15%
10%
5%
0%
Percentage of VAF
35.78%
13.04%
8.57%
6.56%
5.75%
5.10%
4.75%
4.42%
3.94%
3.82%
3.37%
3.08%
1.85%
0
1
2
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6
7
8
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11
12
13
Component

Figure 1

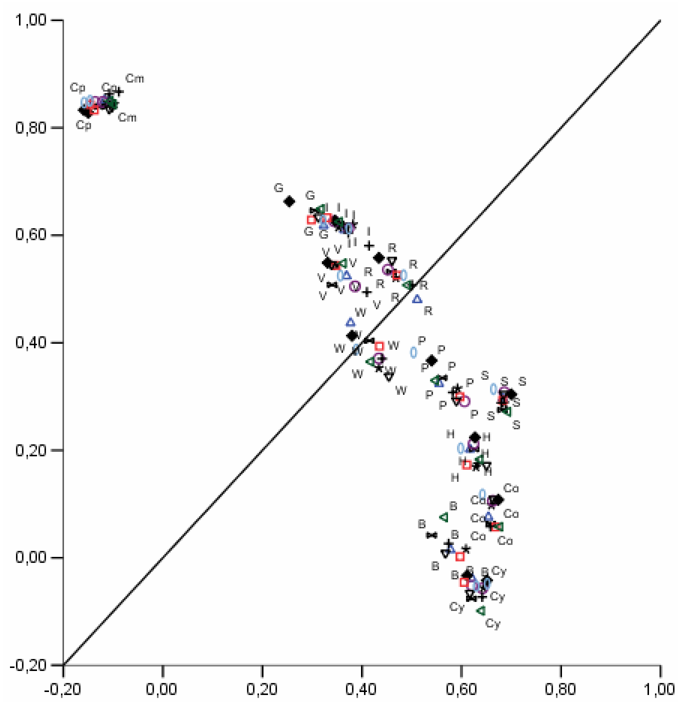

Figure 2a

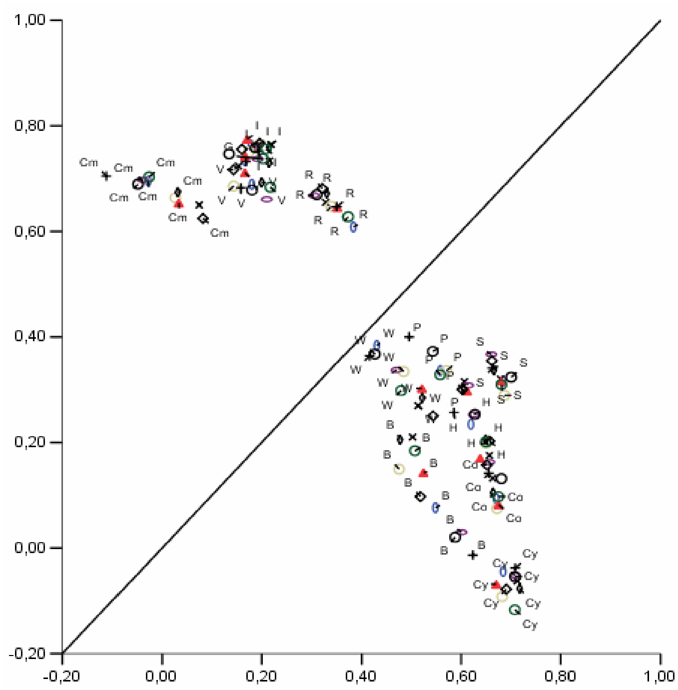

Figure 2b

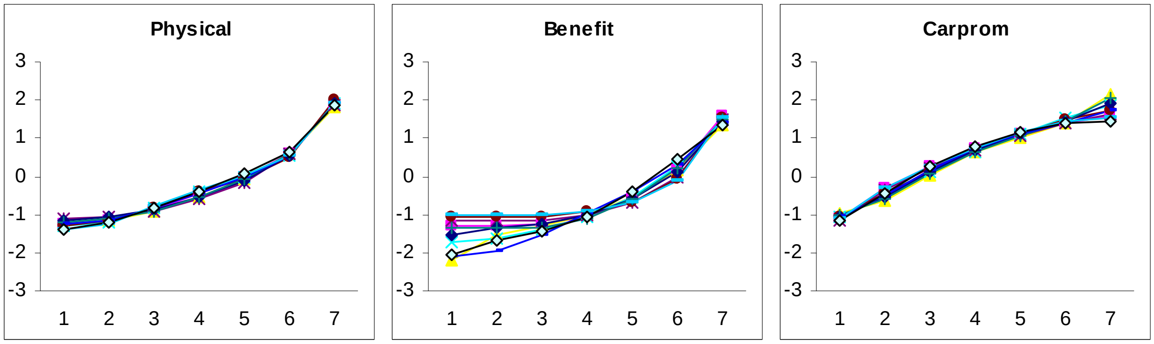

Figure 3

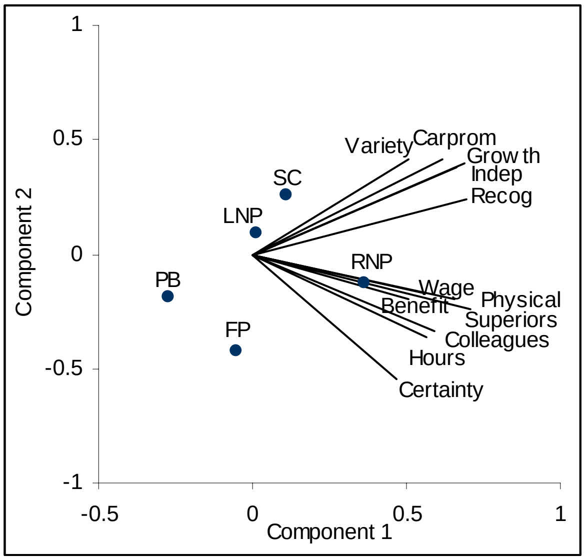
1
0.5
0
-0.5
-1
-0.5
0
0.5
1
Component 2
Component 1
Variety
Carprom
Grow th
Indep
Recog
SC
LNP
RNP
Wage
Physical
Benefit
Superiors
Colleagues
Hours
Certainty
PB
FP

Figure 4