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Identifying the Component Structure of Satisfaction Scales by Nonlinear Principal Components Analysis

Marica Manisera[1], Anita J. van der Kooij[2] and Elise Dusseldorp[3]

[1]Department of Quantitative Methods, University of Brescia, Italy
[2]Data Theory Group, Department of Education, Leiden University, The Netherlands
[3]TNO Quality of Life, Department of Statistics, The Netherlands
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Abstract: The component structure of 14 Likert-type items measuring different aspects of job satisfaction was investigated using nonlinear Principal Components Analysis (NLPCA). NLPCA allows for analyzing these items at an ordinal or interval level. The participants were 2066 workers from five types of social service organizations. Our results suggest that taking into account the ordinal nature of the items was most appropriate. On the basis of a stability study, a two-component structure was found, from which we extracted two subscales ("Motivation" and "Hygiene") with reliabilities of .81 and .77. A Multiple Group analysis confirmed this structure. We also investigated whether workers in the five types of organizations differed with respect to the component structure, employing a feature of the program CATPCA. We found that the organizations did not differ much with respect to the job satisfaction components.

Keywords: CATPCA, Herzberg, monotonic transformations, multiple group method, nonlinear principal components analysis, satisfaction survey data, scale construction.

1. Introduction

In the social and economic sciences, numerous studies have investigated which factors affect the quality of services and products supplied. The literature about the quality of services and products underlines the opportunity to consider both customer and job satisfaction (among others [10, 15, 28, 30, 31]). The underlying idea is that a better organizational climate (and then, a higher job satisfaction) is related to a higher customer satisfaction. A study focusing on customer or job satisfaction requires a good measurement of the concept, which can be difficult to establish. First of all, there are some problems directly linked to the subjective nature of satisfaction data. 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 [1].

Secondly, the measurement of 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 satisfaction in a questionnaire [33, 34].

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 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 [20], 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 [7, 40]. 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 customer or 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.

Standard 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. In the social and behavioural sciences many variables are categorical (nominal or ordinal) and relationships between variables are frequently nonlinear, so, for categorical data standard PCA is often not the most appropriate analysis method.

To avoid the limitations of standard PCA, Nonlinear PCA [1] (NLPCA) has been introduced and developed during the last 40 years [7, 21]. NLPCA does not make assumptions concerning the measurement level of the variables and the nature (shape) of their relationships, but analyzes the data at a level specified by the researcher (interval, ordinal, or nominal), resulting in quantifications of the categorical variables that reveal the shape of the relations between them.

Although in satisfaction survey it is common practice to analyze Likert scale data as if they were of interval level, one could question whether this is appropriate. When applying NLPCA with ordinal scaling level, quantified values are obtained for the categories that respect the rank order, but do not necessarily have equal intervals. So, treating the variables as ordinal in NLPCA will reveal whether or not the variables can be treated as interval data: if the values of the ordinally quantified variable have (about) equal intervals, standard PCA

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[1] In this paper we restrict the general term nonlinear PCA to refer to the optimal scaling approach to nonlinear PCA.

would be appropriate. Another advantage of NLPCA above standard PCA is that background (grouping) variables, like sex, marital status, age, region, *etc.*, can be included in the analysis to examine the relationship of the categories of such variables to the component structure.

In the present study we employ NLPCA to identify the component structure of job satisfaction taking into account the ordinal nature of the data, and to summarize the data contained in numerous items into one or more subscales of job satisfaction that can be used in further models.

We will investigate whether the component structure found by NLPCA is stable, using a number of samples randomly drawn from the data. We will also investigate if the structure can be confirmed using the multiple group method (MGM; [14, 27]) on a test sample. And, finally, we will examine whether different types of organizations are differently related to the component structure. The focus of this study is on job satisfaction, but the very same kind of study could be replicated for customer satisfaction survey data and any other survey data related to subjective attitudes of individuals.

2. Organizational Context

Our dataset was collected in a survey[2] described by Borzaga [2] and coordinated by ISSAN (Istituto Studi Sviluppo Aziende Nonprofit) of University of Trento. 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.

3. Method

3.1. 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

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[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.

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 were 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.

3.2. 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 five categories (see end of the previous section), and missings for 110 workers. These missings are not relevant for the analysis because the variable Type was used as a supplementary variable in the analysis, that is, it was not included in the analysis but it was fitted in the solution found for the analysis variables. 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.

3.3. Statistical Method

We used the program [4] CATPCA (CATegorical Principal Components Analysis) implemented in the Categories module of SPSS [24], which is an implementation of the optimal scaling approach to NLPCA. This approach 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 [21]. The NLPCA model is the same linear model as in traditional PCA, but it is applied to nonlinearly transformed data. So, all the nice mathematical properties of PCA also hold in NLPCA. The variables are transformed by assigning optimal scale values to the categories, resulting in numeric-valued transformed variables. NLPCA 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. The NLPCA method is especially suitable for the 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.

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) are based upon properties of the transformations (non-monotone, monotone, linear) of the variables. The analysis level of a variable, which is chosen by the researcher, defines the form of the transformation for a variable, and it does not need to be equal to the measurement level of a variable [7]. In this paper, we will refer to the analysis level as the scaling level.

Nonlinear transformations can be nonmonotonic or 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 [25].

3.4. 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 (it is common practice that the training set contains a majority of the data, frequent choices are 0.70*N*, 0.75*N*, or 0.80*N* for training and 0.30*N*, 0.25*N*, or 0.20*N* for testing; [19, 11, 8]). Because the response scale of our items are ordered categories, and the meaning of the order is the same for each item (higher category = being more satisfied), three different scaling levels were chosen: ordinal, spline-ordinal (we used second degree monotonic splines with two interior knots; see [29]), and numeric. Comparisons of the solutions for the training set obtained with these different scaling levels were based on the Total Percentage of Variance-Accounted-For

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

(Total PVAF) in the transformed variables, on Cronbach's α [5] 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 discarding variables that are the most instable. But, categories with a low frequency are likely to be instable, causing instability of the variable and the solution. Such categories can be merged with an adjacent category to reduce the instability of a variable (see for a detailed discussion [22]).

The subscales of job satisfaction are computed as the simple sums of the transformed values of variables with high rotated loadings on a specific principal component. The reliability (Cronbach's α) of these subscales was assessed, and the Pearson correlation coefficient between subscales was computed.

Then, confirmatory principal components analysis using the multiple group method (MGM; [14]) was applied to investigate whether the subscales as suggested by CATPCA were 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, the a priori idea comes from 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 for the items within each subscale (*i.e.*, the correlation between a particular item and the subscale the item is assigned to, but excluding the item from the subscale). To correct for the subscale length (*i.e.*, the number of assigned items) the formula suggested in Guilford [9] was used. Although other methods of confirmatory analysis (for example, the confirmatory common factor approach, [16, 17]) 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 [36].

In addition, we investigated whether the five different types of organizations show differences with respect to the 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 component scores of the persons that scored the category, thus in our case, the persons that belong to a specific type of organization. The joint plot of category (group) 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 relate in about the same way to the other variables.

4. Results

On the training set, we performed three CATPCA analyses with two components[5] with different scaling levels: ordinal, spline ordinal, and numeric. Table 1 shows the fit indices for each scaling level.

Table 1. Percentage of variance-accounted-for (PVAF) and VAF (Eigenvalue) obtained by CATPCA with two components selecting ordinal, spline ordinal, and numeric scaling levels applied to the training set.

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

In terms of PVAF and Cronbach's α, the 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 spline-ordinal and ordinal solutions was also reflected in the transformation plots. We chose the spline ordinal scaling level, because we preferred the more parsimonious (more restrictive) transformations. 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 (see Appendix A), 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 and the Scree test [4]. In an initial CATPCA for the training set with the maximum number (13) of components the first three eigenvalues were greater than one. Then, we performed a CATPCA with three components to check the sizes of the eigenvalues 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. In CATPCA, the correlations between the transformed variables 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.

[5] The number of components is in line with previous work [3].

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.

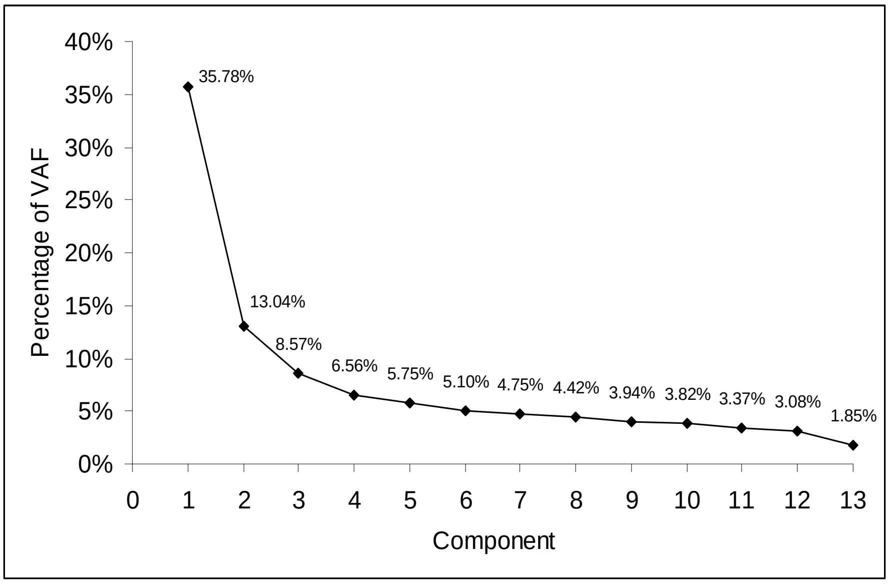


Figure 1. Screeplot of the 3-component CATPCA solution.

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 [18]. The rotated components remain uncorrelated with this type of rotation. The optimal transformations for the unrotated solution are also optimal for the rotated solution because transformations are invariant under rotation. We inspected the rotated 3-component solution and the rotated 2-component solution (Table 2). 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 third component of the 3-component solution included only two variables, Carprom and Carprosp (with component loadings in the rotated solution equal to .861 and .858 respectively). Nevertheless, two variables with high loadings are, in general, too few to form a separate component [35]. Therefore, we decided to use the 2-component solution.

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 2), indicating they also fitted well in the 2-component solution. In accordance with the solution in Table 2, we could consider two subscales: the first one including aspects related to the environment in which people work, and the second one including aspects related with the work itself (see numbers in bold face in Table 2).

Table 2. Rotated component loadings of the 2-component CATPCA solution for the training set.

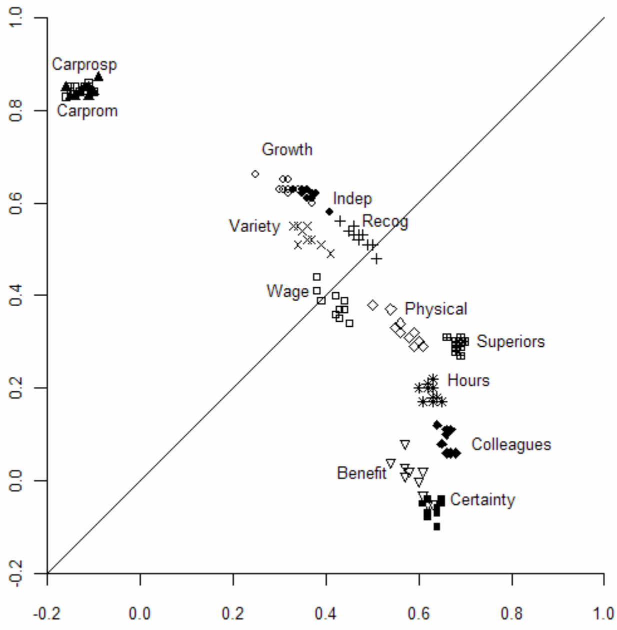
	Component	
	1	2
Growth	.353	**.615**
Indep	.382	**.620**
Recog	.468	**.521**
Variety	.350	**.543**
Physical	**.592**	.315
Benefit	**.609**	.016
Wage	**.434**	.353
Hours	**.629**	.169
Carprom	−.098	**.844**
Carprosp	−.112	**.848**
Certainty	**.644**	−.056
Superiors	**.686**	.287
Colleagues	**.660**	.097

Note: The strongest correlation of a variable to a component appears in bold.

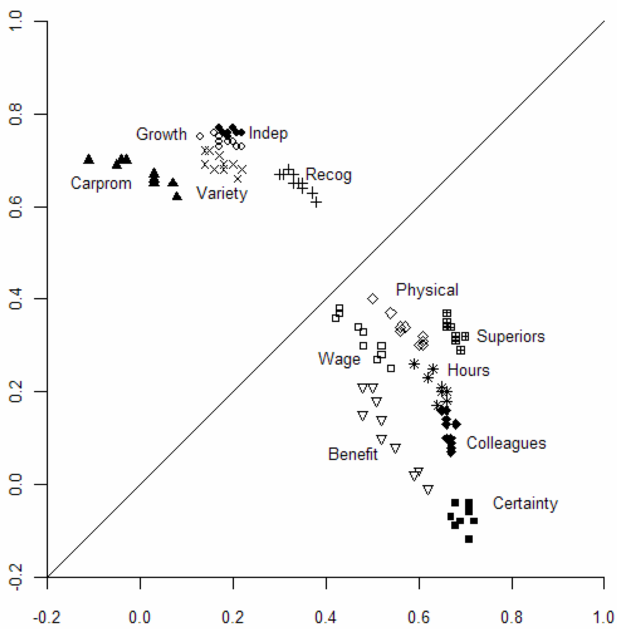
The stability of the above-mentioned CATPCA results was studied using ten random samples of size 0.75*N* (including the training set). The solution with spline ordinal was always preferable (with regard to the goodness-of-fit indices) to the solutions with other scaling levels in the 2-component solution. 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 component 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.

The stability of a solution is reflected in the spreads of the ten component loadings for each variable. If the solution is stable, the spread for all variables is small in both dimensions. In Figure 2(a) we see that for all variables the ten loading points form rather tight clusters, so we can conclude that the solution is stable.

To evaluate the consistency of the assignment of variables to components, we inspected the position of the ten loadings for each variable in relation to the reference line. The reference line indicates the position of loadings that are equal on both components. Thus, if a loading for a variable is above the reference line, it means that the variable loads higher on the second component than on the first 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 consistent component structure is obtained if for all variables all the 10 points are on the same side of the reference line; in that case, the assignment of variables to subscales is the same for each random sample.



(a)



(b)

Figure 2: Loadings of the 13 satisfaction variables in the rotated 2-component CATPCA solution obtained with 10 random samples ($0.75N$) (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 2(a) shows that the solution is stable, but that for variables Wage and Recog not all ten points are on the same side of the reference line, so the assignment of these variables to the subscales will vary in the ten samples.

The inconsistency in the component structure was most probably due to the high correlation ($r = .74$) between the variables Carprom and Carprosp, relative to the intercorrelations of the other variables (varying between .09 and .52). Because of this, Carprom and Carprosp form a unique career component in the 3-component solution of every random sample and they dominate the second component component in the 2-component solution (their loadings on the second component are substantially higher than the loadings for the other variables loading high on this component). The strong influence of the career aspect on the second component can be diminished by discarding one of the career variables from the analysis. 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 removed the inconsistency in the assignment of the variables Wage and Recog. In Figure 2(b) we see that all loadings for these variables are on the same side of the reference line now.

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 3 shows the corresponding loadings.

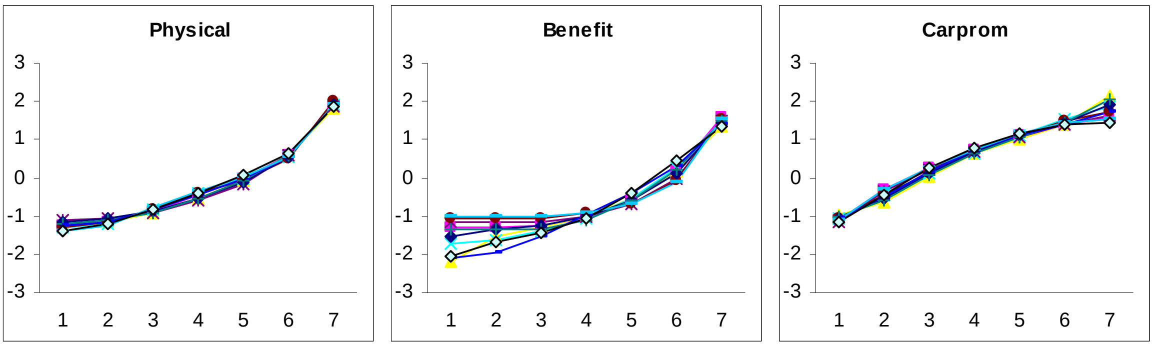


Figure 3: Transformation plots of the variables Physical, Benefit and Carprom obtained with 10 random samples (0.75*N*) after excluding variable Carprosp.

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 3). 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 4) 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 4). 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.

A reliability analysis applied to the transformed variables showed no need to delete an item: $\alpha = .774$ in the training set and .748 in the test set for the first subscale, and $\alpha = .790$ 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.

Table 3. Rotated component loadings of the 2-component CATPCA solution (without Carprosp) for the training set.

	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

Note: The strongest correlation of a variable to a component appears in bold.

With reference to the five different types of organizations, the CATPCA plot of loadings and category points (Figure 4) showed that the five group points lay rather close together around the origin. Thus, we concluded that the five types of organization do not differ much with respect to the component structure of job satisfaction found by CATPCA.

Table 4. Correlations between the transformed variables and the two subscales of job satisfaction in the test set.

			Correlations corrected for subscale length	
	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

Note: The table shows the item-rest correlation if an item belongs to a subscale and the item-total correlation otherwise.

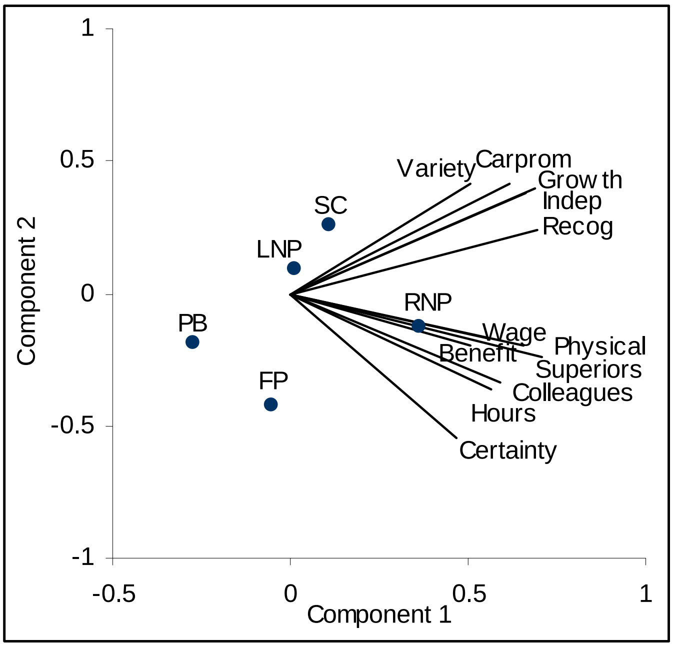


Figure 4. Loadings of the 13 satisfaction variables (vectors) and five category points representing the five types of organization: SC = social cooperatives; FP = for profit; PB = public bodies; LNP = lay non profit; RNP = religious non profit.

5. 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 taking into account the ordinal nature of the data. 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 NLPCA (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 in the same analysis if responses from several types of organizations 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.

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 [12]. 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" [13], 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 [39]. Unlike some of those instruments, such as the Emergency Physician Job Satisfaction Scale [23], 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 [32]).

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 (among others [6, 26, 38]). Some authors consider PCA as a method of FA [38]; whilst other scholars think that they are conceptually very different [6]. 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 [37]. If one is interested in a theoretical solution and wants 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 [37]. 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 [6, 38].

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, nor are subjects pairwise deleted, but missings are handled in the CATPCA algorithm by differential weighting of the transformed variables in estimating the component scores (this strategy is possible because CATPCA computes the solution from the data itself; not from the correlation matrix as in traditional PCA).

Although we preferred to apply the passive strategy, because it does not replace missings with (possibly unstable) imputations, we used mode imputation for the purpose of obtaining the rotated solution for the transformed variables with a traditional PCA technique. When applying the passive missing strategy, the transformed data matrix will have missings where the original data matrix has missing. We computed the correlations between the component scores obtained using the mode imputation strategy and using the passive strategy to check to what extent the mode imputation affected the solution. The correlation coefficients were high (.985 for the first component and .880 for the second component), indicating that the solution for mode imputated data much resembled the solution for unimputed data.

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 and the aim is to link job and customer satisfaction in order to determine the quality of services form both points of view (worker and consumer).

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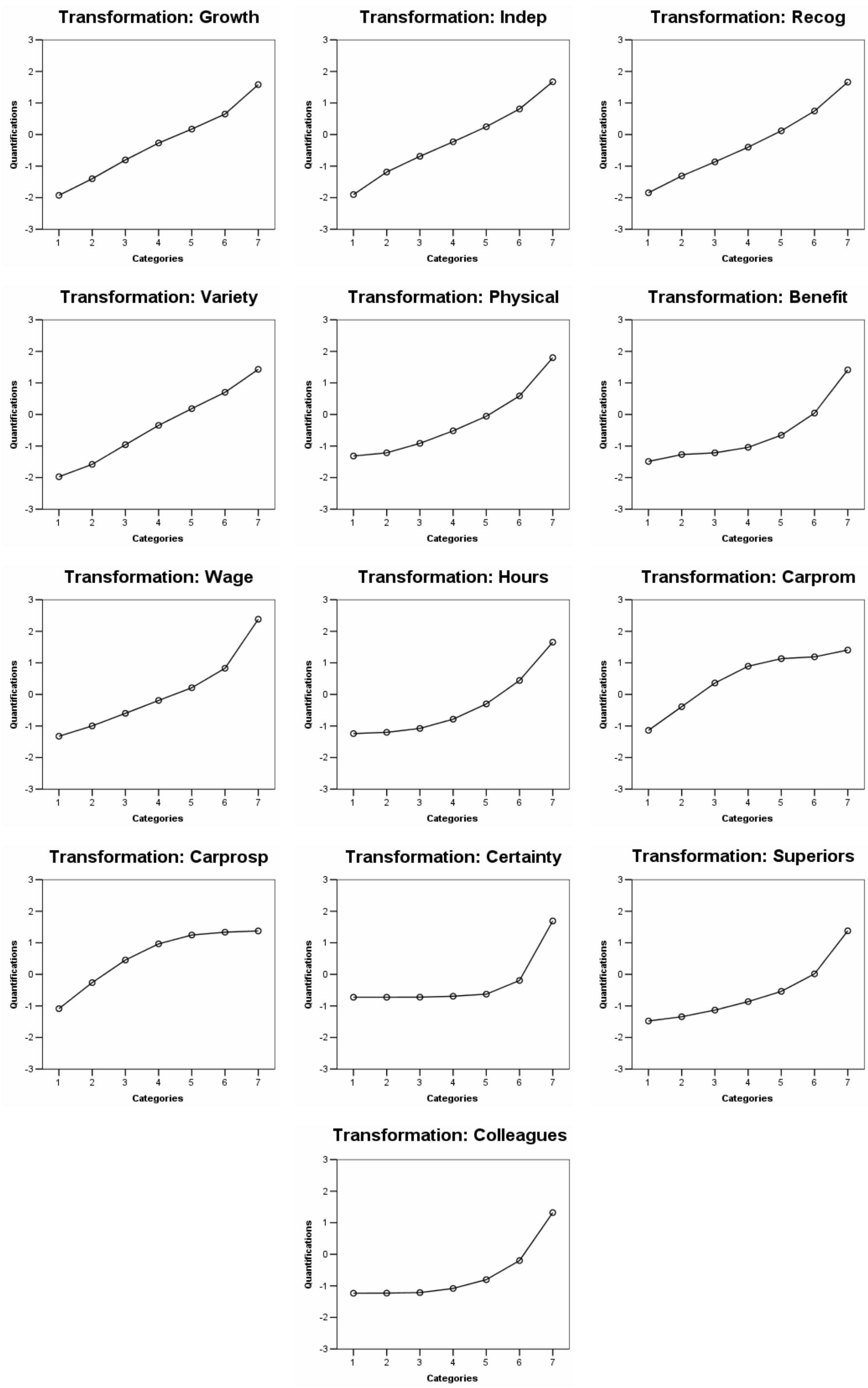
Appendix A

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



Authors' Biographies:

Marica Manisera, PhD, is a researcher at the Department of Quantitative Methods, University of Brescia, Italy. From 2005 to 2009 she was post-doctoral fellow at the same department. In 2005 she received her PhD degree in Methodological and Applied Statistics at the University of Milano-Bicocca (title of thesis: "Measuring job satisfaction by means of Nonlinear Principal Component Analysis". Advisors: Prof. M. Carpita and Prof. M. Civardi). In 2003 she was lecturer in Statistics at the University of Milano-Bicocca; from 2004 she has been lecturer in Statistics, Data Analysis, and Data Mining at the University of Brescia. Her research interests include the statistical methods and models for the evaluation of the quality of work and customer satisfaction; measuring nonlinearity in data analysis; minimax estimation methods in time series; missing data imputation techniques.

Anita J. van der Kooij, PhD, is a researcher at the Department of Education, Data Theory Group, Leiden University, The Netherlands. Her research interests are optimal scaling techniques for multivariate analysis, and software development. She can be reached at kooij@fsw.leidenuniv.nl. For publications, see her personal page at www.datatheory.nl/pages/kooij.html

Elise Dusseldorp, PhD, was during the main part of this research Assistant Professor at the Department of Education, Data Theory Group, Leiden University. From September, 2007, she works as a statistician at the Netherlands Organization of Applied Scientific Research: TNO, division Quality of Life. She received her PhD degree in the Social and Behavioral Sciences (2001) at Leiden University. Title of thesis: "Discovering treatment covariate interaction: An integration of regression trees and multiple regression". Advisors: Prof. J.J. Meulman and Prof. S. Maes. From 2002-2006 she was post-doctoral fellow in the VENI-project "Modeling interaction effects as small trees in regression and classification". Her research interests are interaction effects (moderators) in regression analysis, classification and regression trees, differential treatment effectiveness, aptitude-treatment-interaction, and optimal scaling. For publications, see her personal page at www.datatheory.nl/pages/dusseldorp.html