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Simple Robust Method for Quasi-Confirmatory Factor Analysis (Three Examples)

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A B S T R A C T

In this article we present a simple robust method named Quasi-Confirmatory Factor Analysis (QCFA), with the purpose of comparing two factor structures, obtained by using exploratory factor analysis (EFA). EFA and CFA (confirmatory factor analysis) approaches, together with other methods that are used in this field, are often used simultaneously in cross-cultural research in testing the possibility of generalizing imported theoretical constructs on different sample of subjects. In the discussions about the matter 'is it better to use EFA or CFA?', it is the most correct to say that each strategy is appropriate for certain research situations. QCFA is conceptually closer to EFA than to CFA, but it gives the exact numerical indicators of the differences, as well as the correlations, between these two factor structures in the final phase of EFAs. The details on the practical application QCFA are presented in three different examples. The advantages and shortcomings of this method are discussed, together with its possible extension.

Key words: *comparing factor structures, exploratory and confirmatory factor analyses*

Introduction

The purpose of this article is to offer one simple and robust method for comparing two factor structures, obtained by using exploratory factor analysis (hereinafter EFA). The related method, named quasi-confirmatory factor analysis (hereinafter QCFA), gives numerical indicators of the differences, as well as the correlations (for the sake of simplicity, in the remaining part of the article correlations will be treated as »similarities«), between these two factor structures. To explore the logic of QCFA, the main terms in FA have to be mentioned.

Factor analysis (hereinafter FA) is a collection of methods used to examine how underlying constructs influence the responses on a number of measured variables: these are called latent variables[1]. FA (in this article, for the sake of simplicity, FA and principal component analysis are used as synonyms) has two main goals: to determine latent factors in the base of the correlations of many manifest (in this case, health-related) variables, as well as to determine the correlations between certain manifest variables and factors obtained[1]. FA has two important practical purposes: FA is a tool to determine construct validity for the questionnaire-based measuring instruments (such as psychological personality inventories, for example) (1); to determine the structure for the set of variables that can explain the pattern of nutrition habits, certain components of metabolic syndrome, etc. (2)[1]. There are two main strategies in applying FA: EFA and confirmatory factor analysis (hereinafter CFA). EFA has the task of *exploring* the factor structure, namely how the variables are related and grouped. It is based on inter-variable correlations and leaded with *empirical data* (statistical results). CFA has the aim of *confirming* the factor structure that has previously been extracted in the EFA: it might be said that it is leaded with *theory*, because it tests previously obtained constructs (using EFA)[1]. CFA is often used to examine the expected causal links between variables: it is a test of the degree of fit between a proposed structural model and the emergent structure of the data[2]. In general, CFA is a preferred approach when measurement models have a well-developed underlying theory for hypothesized patterns of loadings[2].

The CFA is used in the most cases, while the use of EFA is declining, in recent articles appearing in the major organizational research journals[3,4], but even in other journals until now, almost 20 years later. Supporters of CFA tend to believe that researchers necessarily need to

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have a strong theory underlying their measurement model before analyzing data[5]. On the other hand, supporters of EFA approach claim that CFA is maybe too often applied as a »scientific fashion«, frequently used in inappropriate situations: they say that CFA is still being used with little theoretical foundation, while the reviewers often require CFA where EFA as a simpler alternative would be as or more appropriate[3]. There are two the main reasons to favor EFA instead of CFA. First, the results of CFA are sometimes misinterpreted to support one structural solution over any other, but it can be a very weak conclusion, especially when only a few of the many possible factor structures were assessed, for a certain theoretical construct, in a specific population[2]. Second, in the situations when the same factor structure is obtained in successive EFA procedures (for different samples of participants), EFA can be considered more convincing and providing stronger evidence for certain factor structures than an unreplicated constrained CFA[1].

However, it is the most accurate to say that each method is appropriate in different situations. EFA may be appropriate for scale construction (constructing measuring instruments), while CFA would be preferred in the cases when measurement models have very good and multiply examined underlying theory for hypothesized patterns of loadings[3]. EFA is often considered to be more appropriate than CFA in the early stages of scale construction: CFA does not show how well the items load on the nonhypothesized factors[6]. It seems reasonable that the series of the research would start with studies that utilize EFA, while later (after several replications) the work would include CFA for the purpose of confirming previous EFA findings on a certain set of data[7]. For example, the study that used Monte Carlo methods found that EFA can contribute to model specification when it is used prior to cross-validation using CFA[8].

The need for agreement about a set of standard EFA and CFA procedures that researchers can use as a guide, as well as the reviewers in evaluating manuscripts was proposed because of the following issues: when to use EFA and when to use CFA (1); to determine the role of CFA in scale development (2); is it useful to use both EFA and CFA on the same data set (3); could the CFA results be the indicators for the changing of the model (4); is it appropriate to »force« the models into a preset number of factors (5)[2]. Meanwhile, it seems that strict standards which would give an exact answer to these needs for agreement are still not defined.

However, EFA and CFA approaches, together with new emerging methods, are often used simultaneously in cross-cultural research in testing the possibility of generalization imported theoretical constructs on different samples of subjects[9]. For example, in order to demonstrate the value of a multiple data analytic approach for testing the cross-cultural generalizability of a Big Five personality measure, by examining structural or construct equivalence, the three above mentioned analytic approaches were compared: exploratory factor analysis, simultaneous component analysis and confirmatory factor analysis[10]. A comparison of latent structures, obtained by using different methods, confirmed the same basic five factor structures across the four country samples, but these methods also showed some differences in the conclusions that could be drawn from the analyses[10].

Comparing Factor Structures

Very often, comparing factor structures in certain data sets in repeated EFAs (at different samples of entities) is mainly reduced to the verbal interpretation of the factor structures in certain research with a fixed number of factors[11], or without limitations in the number of factors[12]. The researcher simplified look at the items that saturate one factor (or complete factor structure in total) in the first data set and then gives the interpretation of one factors (or complete factor structure) in the second data set. Finally, the researcher gives an interpretation of the differences in factor structures in two sets of data, in general and/or separately for each sample.

There are several methods to obtain exact indicators of the similarity of factor structures, using EFA approach. Three of these methods will be described here. A simple Pearson r can be used to compare a factor in one group with a factor in a second group: Pearson r coefficient can detect the differences in two factors' patterns of loadings, as well as differences in the relative magnitudes of those loadings[13]. The shortcoming of this method is that one should beware that with factors having a large number of small loadings, small loadings could cause the Pearson r to be large (if they are similar between factors) even if the factors had dissimilar loadings on the more important variables[13]. In other words, this method includes the whole factor loadings in the comparison in the first phase of the factors' extraction, in spite of its insignificance. The second method is Tucker's Coefficient of Congruence, which is based on multiplying each loading in one group by the corresponding loading in the other group: sum of these products is then divided by the square root of: a value in the range 0.85–0.94 corresponds to a fair similarity, while a value higher than 0.95 implies that the two factors or components compared can be considered equal[13]. Third and the most sophisticated method for comparing the principal components or factors, which analyze the differences in complex (often longitudinally obtained) datasets is the analysis of variance-simultaneous component analysis (ASCA or ANOVA–SCA)[14–18]. It is a method that partitions variation and enables interpretation of these partitions by simultaneous component analysis, in a way similar to principal components analysis (PCA). Each partition matches all variation induced by an effect or factor, usually a treatment regime or experimental condition (it is in fact megavariate ANOVA): calculated effect partitions are called (multivariate) effect estimates[14]. Simplified, it is a direct generalization of the analysis of variance (ANOVA) for univariate data to the multivariate case[14,16]. For example, in functional genomics, experimental designs are used to generate the data: the resulting data sets are organized according to this design and for each sample many biochemical compounds are measured (typically thousands of gene-expressions or hundreds of metabolites). This results in high-dimensional data sets with an underlying experimental design: ANOVA–SCA is one of several methods that have recently become available for analyzing such data while utilizing the underlying design[14]. However, when perform EFA to obtain interpretable factor structure for certain theoretical construct, both (psycho) metric and interpretability criteria have to be followed. Both Pearson r and Tucker's coefficient of congruence deal with the first phase of factors' extraction in FA, where all the variables are included in the factor structure (even if some variables do not saturate the factors highly enough, for example, at least with the correlation of 0.30). After »cleaning« (omitting) variables that unsatisfactorily saturate the factors (irrelevant if it depends on the interpretability or metric criteria), some variables in two factor structures that have to be compared will miss. In such cases, in this article we propose a simple robust method for comparing factor structures, which is named Quasi-Confirmatory Factor Analysis (hereinafter QCFA). QCFA deals with comparing two factor structures obtained by EFAs, with fixed number of factors (for example, four). QCFA is as simple as Person r method, but it makes up for some shortcomings of Person r method.

Quasi-confirmatory Factor Analysis (QCFA): Basic Assumptions

The concept of QCFA is much closer to EFA than to CFA. As it was already mentioned above, after several replications of EFA, CFA can be used to support or reject theoretical model (established using replicated EFA procedures, on different samples of participants), on certain sample of research data. QCFA can be seen as EFA or CFA: QCFA is leaded by statistical results (use the results of EFAs and compare them), but it also tries to follow a theoretical model (giving fixed number of factors in advance). The most simplified, QCFA says that some factor structures obtained in the last phase of factors' extraction in EFAs (which are compared) are similar or different, using adequate correlation measures and/or statistical tests to compare the differences. The method of factor extraction is the same in Pearson r comparison and in QCFA, but only in the first phase of factors' extraction, where all manifest variables are included in the analysis. QCFA deals with the last phase in EFA, when all chosen metric criteria (for example, Scree Plot and Kaiser-Guttman's criterion), both with interpretability criterion, are satisfied simultaneously. However, it is impossible to include the quantitative loadings of all the variables in factor comparing, if we are dealing with further steps (after the first phase of factors' extraction) in EFA, when some variables are missing. Consequently, in QCFA a solution made by binarized loadings is proposed. At all the variables that are dropped-out from factor structure(s) in both datasets which are compared, both unsatisfactory loadings (for example, factor saturations lower than 0.30) and missed variables (with belonging missed loadings) are replaced with zeroes (0). So, the main difference between QCFA and Pearson r is the fact that QCFA deals with binarized loadings and not with their quantitative values: an obvious shortcoming of QCFA in this context is a higher probability of making Type II error (false negative: the failure to reject a false null hypothesis). The advantage of this solution is that it compensates for the previously mentioned shortcoming of Pearson r method (Lorenzo-Seva and ten Berge, 2006). The other advantage is the fact that QCFA offers the possibility for two types of comparisons (using correlations and/or differences), using statistical measures for binary variables. The fact that QCFA is comparing variables (with belonging binarized loadings) and not cases, lead to the conclusion that using QCFA we are dealing with paired (related) samples of data. Although we are comparing two different datasets (obtained from different subjects), we are expecting the positive correlation between two (or more) belonging loadings in comparable EFA produced factors. As in Pearson r comparison, in QCFA it is also the most correct to compare directly only similar factors (i.e. those which are highly loaded with the most similar variables). For this purpose, the easiest way is to count the number of variables which are the same in the first factor structure and then in the second factor structure: the factors with the most similar variables could be compared in QCFA. Then, the nonparametric statistical tests for related (dependent, paired) samples are used to test the differences among compatible factor structures in both datasets, while nonparametric correlations for nominal variables are used to find a correlation among compatible factor structures in both datasets.

When resuming the QCFA procedure, it is important to use the same method of EFA for factor extraction and rotation in both datasets: e.g. PCA with Varimax rotation. Furthermore, in both datasets, fixed (the same) number of factors, with the same criterion for minimal factor loadings (e.g. 0.30). Finally, in both datasets, factor loadings (saturations) have to be binarized: transformed in sufficient (1) and insufficient (0). Among the basic prerequisites for QCFA, two can be emphasized: similar number of entities (i.e. cases, not variables) in both sets of variables (1^{st}) and satisfied conditions for EFA (e.g. ratio between the number of variables and the number of entities, the number of entities in general) (2^{nd}). The second prerequisite is obligatory, while the first implies that the dataset with much smaller number of cases can provide a lower possibility of generalization.

Main shortcomings of QCFA could be summarized in three main points: QCFA is very simple and rough method for comparison two factor structures, which neglects subtle differences among them (because of binarization) (1^{st}); QCFA depends not on the number of entities, but on the number of variables that are compared – small number of variables can cause Type II error in nonparametric differences' testing or correlating two compatible factor structures in two datasets (2^{nd}); strict basic prerequisites are simultaneously the main shortcomings of QCFA (3^{rd}). However, QCFA has the same limitations as nonparametric statistical methods in general.

The advantages of QCFA could be considered in four points: it is a very easily usable method for comparing two samples about the same construct (1^{st}); it keeps some benefits of EFA, analysing the latent structures of empirical data, obtained with EFA (2^{nd}); it gives more precise insight in the similarities of two latent structures of the same construct in two datasets, obtained by EFAs than interpretative comparison, having some characteristics of CFA, giving some exact indicators of these similarities, but not based on the regression model (such as CFA), but in terms of differences and correlations (3^{rd}); QCFA could be especially useful in preliminary studies or in situations when exact comparison of factor structures in not an important goal of the research (4^{th}). Basic differences among QCFA wirh EFA and CFA procedure are described in Table 1.

Use of QCFA – Three Examples

Three examples are presented to illustrate the easiness of using QCFA, together with its advantages and shortcomings, mainly raised from the number of variables in certain datasets.

First example: stress in nurses and criminalists

The first example is using the results of study about perceived stress, where two samples are examined: the first one consists of 75 students of Nursing on the University of Dubrovnik (14 male and 61 female); the second sample comprises 63 students of Criminology on the Police Academy in Zagreb (49 male and 14 female). The measuring instrument named Stress test[19] has 8 items: it is usually scored as a sum of estimations on each of items. However, in this research, author wanted do detect specific factor structures adjusted to certain samples. On the base of Scree Plot, two-factor structure has emerged. Kaiser-Meyer-Olkin Measure of Sampling Adequacy (0.787) and Bartlett's test of Sphericity (χ^2=129; df=28; p<.01) showed that correlation matrix is good for factorization in the sample of nurses. For the sample of criminalists, the same indicators are worse, but still enough satisfying: Kaiser-Meyer-Olkin Measure of Sampling Adequacy (.575) and Bartlett's test of Sphericity (χ^2=54; df=28; p<.01). Principal Component Analysis (Table 2) and a Scree plot of the component structure indicated in both samples a steep drop of eigenvalues that revealed a two-component structure, with principal components of perceived group cohesion named: exhaustion and limited self-control (1) and diet and sleep difficulties (2). In the sample of nurses, both components accounted

TABLE 1
A COMPARISON BETWEEN THREE TYPES OF FACTOR ANALYSES (EXPLORATORY, CONFIRMATORY AND QUASI-CONFIRMATORY)

EFA Steps	CFA Steps	QCFA Steps
Collect data (measure variables on the same, or matched, research units)	Review the relevant theory and research literature to support model specification	Collect data (same as in EFA)
Obtain the correlation matrix, between each of variables in the same set	Specify a model (e.g., diagram, equations)	Obtain the correlation matrix, between each of variables in the same set (same as in EFA)
Fix the the number of factors for inclusion on the base of criteria for factor (e.g. using Scree Plot test)	Determine model identification (e.g., if unique values can be found for parameter estimation; the number of degrees of freedom, for model testing is positive)	Fix the the number of factors for inclusion, *on the base of previous research*
Extract initial set of factors (e.g. using Principal Components method)	Collect data (measure variables on the same, or matched, research units)	Extract initial set of factors (same principle as in EFA)
Rotate the factors obtained, to get factor solution that is equal to that obtained in the initial extraction but which has the simplest interpretation (e.g. Varimax)	Estimate parameters in the model	Rotate the factors obtained (same principle as in EFA)
Interpret the factor structure obtained	Assess model fit	Interpret the factor structure obtained (same principle as in EFA)
Define factor scores for further analysis	Present and interpret the results	*Find the most similar factor structures as in the previous research (compatible factors in two datasets)*
		Define binary coded factor loadings in certain datasets for all the variables, but in the last phase of factor extraction
		Correlate or/and find diferences between variables that depend to each factors in both sets

Legend: EFA- exploratory factor analysis; CFA- confirmatory factor analysis; QCFA – quasiconfirmatory factor analysis

TABLE 2
DIFFERENCES AND CORRELATIONS AMONG COMPONENTS STRUCTURE OF STRESS IN TWO DIFFERENT SAMPLES (NURSES AND CRIMINALISTS)

Items	Nurses		Criminalists	
	Exhaustion and limited self-control	Diet and sleep difficulties	Exhaustion and limited self-control	Diet and sleep difficulties
Do you eat quickly		0.710	–	–
Are you often feeling exhausted or ill	0.839		0.677	
Do you feel too tired for any additional physical activity	0.825		0.459	
Do you have trouble with sleeping or getting out of bed	0.521		0.505	0.506
Do you have problems with the personal decision to say »no«	0.418	0.460		0.811
Do you feel that your life is out of personal control	0.541	0.568		0.789
Do you eat or drink or smoke excessively when you are tense		0.708	0.750	
Do you skip some meals		0.598	0.563	
Eigenvalue	2.31	1.93	1.83	1.67
Variance Explained	28.82%	24.14%	26.09%	23.87%
Reliability (Cronbach's α)	0.671	0.685	0.539	0.526

BINARIZED COMPARISON – DIFFERENCES TESTS AND CORRELATIONS

Items	Exhaustion and limited self-control		Diet and sleep difficulties	
	Nurses	Criminalists	Nurses	Criminalists
Do you eat quickly	0	0	1	0
Are you often feeling exhausted or ill	1	1	0	0
Do you feel too tired for any additional physical activity	1	1	0	0
Do you have trouble with sleeping or getting out of bed	1	1	0	1
Do you have problems with the personal decision to say »no«	1	0	1	1
Do you feel that your life is out of personal control	1	0	1	1
Do you eat or drink or smoke excessively when you are tense	0	1	1	0
Do you skip some meals	0	1	1	0
Sign test (p)	0.500		1.000	
McNemar Test (p)	0.500		1.000	
Cramer's V	0.600		0.600	
Contingency Coefficient	0.514		0.514	

for 52.96%, while in the sample of criminalists both components accounted for 49.96 % of the total variance explained. All components in both samples (nurses and criminalists) showed low or moderate but satisfying values of reliabilities.

For comparing two factor structures, performing QCFA, firstly the satisfying component loadings (higher than 0.40) are transformed in 1 (one), while lower loadings and those which are omitted after the first phase of factor extraction are transformed in 0 (zero). Using tests of differences, to get an insight in differences in first component of stress (exhaustion and limited self-control) among nurses and criminalists, two nonparametric tests were applied: Sign test and McNemar Test. The same value of both tests ($p=0.50$) indicates the absence of differences in two component structures. When the same tests are applied for the second component (diet and sleep difficulties), the absence of differences is also confirmed ($p=1.00$). Using correlation measures, to get an insight in associations between the two first components of stress (exhaustion and limited self-control) in nurses and criminalists, two nonparametric correlations were calculated: Cramer's V (0.60) and Contingency Coefficient (0.51). Both coefficients were showed to have no statistical significance. The same values of nonparametric correlation (also insignificant) are found between second components of stress (diet and sleep difficulties) in two datasets. Although all indicators of the similarity of factor structures are statistically insignificant, their absolute value shows that there are some differences/correlations among compatible components in two datasets. However, it reflects the shortcoming of QCFA, which is linked with a number of entities (variables) in comparison: at eight variables, only big differences/correlations might be reflected. Namely, in this case, nothing can be concluded beyond doubt about the similarities or the differences among these two structures of two components. (They are not similar, if we follow the logic of insignificant correlations; they are also not different, if we follow the insignificant tests of differences).

In the next two examples, Croatian samples of athletes were examined[20]. Group Environment Questionnaire (GEQ, 18 items in total) and Sport Multidimensional Perfectionism Scale (MSSP, 30 items in total) are applied, on the samples of 223 male Croatian athletes: 107 top basketball players from nine teams in A-1 Croatian Basketball League and 116 recreational table tennis players who play in Table Tennis Organization of Clubs and Actives in Zagreb. Principal Components Analyses were conducted separately in each of two datasets (table tennis and basketball). In both subsamples, Group Environment Questionnaire (GEQ) showed two-component structure: combined social-task cohesion and friendship. In both subsamples, Sport Multidimensional Perfectionism Scale (MSSP)) showed three-component structure: high personal standards, parental pressure and worry about mistakes.

Second example: perceived group cohesion in basketball and table tennis players

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (0.804) and Bartlett's test of Sphericity (χ^2=505; df=136; p<.01) showed that correlation matrix is good for factorization in the sample of basketball players. For the sample of table tennis players, the same indicators are similar, and thus satisfying, too: Kaiser-Meyer-Olkin Measure of Sampling Adequacy (.842) and Bartlett's test of Sphericity (χ^2=615; df=120; p<.01) Principal Component Analysis (Table 3) and a Scree plot of the component structure indicated in both samples a steep drop of eigenvalues that revealed a two-component structure, with principal components of perceived group cohesion named: social-related perceived cohesion (1) and task-related perceived cohesion (2). For the sample of elite basketball players, both components accounted for 40.18 %, while in the sample of recreational table tennis players both components accounted for 43.85% of the total variance explained. All components in both samples (basketball and table tennis players) showed from low to moderate but satisfying values of reliabilities.

For comparing two factor structures, performing QCFA, the same procedure is followed as in the case of stress at nurses and criminalists: first, satisfying component loadings (higher than 0.40) are transformed in 1 (one), while lower loadings and those which are omitted after the first phase of factor extraction are transformed in 0 (zero). Then, the same tests of differences (Sign test and McNemar Test) are used, to find differences in two components of perceived group cohesion (social-related perceived cohesion and task-related perceived cohesion) among elite basketball and recreational table tennis players. Also, two nonparametric correlations were calculated: Cramer's V and Contingency Coefficient. In this case, for both principal components of perceived group cohesion (social-related perceived cohesion and task-related perceived cohesion), all tests of differences among two datasets (top basketball and recreational table tennis players) were insignificant. On the other hand, the statistically significant moderate positive correlations are found among two datasets in the component social-related perceived cohesion (while the correlations among top basketball and recreational table tennis players are not statistically significant in the component task-related perceived cohesion).

This example reflects the fact that QCFA could reflect the differences/similarities in factor structures, at bigger samples of entities (variables) in comparison, together with real existing differences/similarities in factor structures. In this case, it could be concluded with more certainty that similarities (together with the absence of differences) really exist among two datasets in the component social-related perceived cohesion. At the other component (task-related perceived cohesion), conclusions cannot be so clear (absence of statistical significant differences and correlations, such as in the stress example).

Third example: multidimensional perfectionism in basketball and table tennis players

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (.728) and Bartlett's test of Sphericity (χ^2=846; df=351; p<.01) showed that correlation matrix is good for factorization in the sample of basketball players. For the sample of table tennis players, the same indicators are similar, and thus satisfying, too: Kaiser-Meyer-Olkin Measure of Sampling Adequacy (.825) and Bartlett's test of Sphericity (χ^2=1409; df=325; p<.01) Principal Component Analysis (Table 4) and a Scree plot of the component structure indicated in both samples a steep drop of eigenvalues that revealed a three-component structure, with principal components of multidimensional perfectionism in sport situations named: high personal standards (1), parental (coach) pressure (2) and worry about mistakes (3). For the sample of elite basketball players, all three components together accounted for 37.31%, while in the sample of recreational table tennis players all the components accounted for 48.19% of the total variance explained. All components in both samples (basketball and table tennis players) showed low or moderate to high and very satisfying values of reliabilities.

For comparing two factor structures, performing QCFA, the same procedure is followed as in the cases of stress and perceived group cohesion: first, satisfying component loadings (higher than 0.40) are transformed in 1 (one), while lower loadings and those which are omitted after the first phase of factor extraction are transformed in '0' (zero). Then, the same tests of differences (Sign test and McNemar Test) are used, to find differences in three components of multidimensional perfectionism in sport situations (high personal standards, parental pressure and worry about mistakes) among top basketball and recreational table tennis players. The same two nonparametric correlations were calculated: Cramer's V and Contingency Coefficient. In this case, for

TABLE 3
DIFFERENCES AND CORRELATIONS AMONG COMPONENTS STRUCTURE OF PERCEIVED GROUP COHESION IN TWO DIFFERENT SAMPLES (BASKETBALL AND TABLE TENNIS PLAYERS)

Items	Social-related perceived cohesion		Task-related perceived cohesion	
	Basketball	Table tennis	Basketball	Table tennis
I do not like to participate in joint activities of my team	0	0	0.657	0
I'm not satisfied with how often our team plays together	0	0	0.720	0.616
When the season ends, I will continue to hang out with my teammates	0.555	0	0	0.629
My desire to win is not equal to that of the majority of the team	0	0	0.517	0.629
A few of my best friends like to play in my team	0.713	0.536	0	0
This team do not offer enough opportunities for my personal development	0	0	0.680	0.657
I have more fun on the other parties than those that are organized by my team	0.415	0.589	0	0
I do not like the style of play in my team	0	0	0.631	0.655
For me, this team is one of the most important groups that I belong	0.408	0.695	0	0
Our team is a whole in which everyone can achieve own sport goals	0	0.542	0.479	0
To members of our team is not important that we stay together as a single group	0.643	0.638	0	0.407
The players of our team include our joint responsibility for losses or poor performance of our team	0.616	0.408	0	0
The players of our team are rarely found in our team as a community	0.631	0.612		0.480
The players of our team have views similar to my own regarding the conflicts during the team games	0.451	0	0	0.660
Our team would like to enjoy the time until the end of the season	0.556	0.635	0	0
If someone has difficulties during training, we are all willing to help him, so it has time and time again to practice	0.643	0.559	0	0.463
The players of our team are not seen together outside of training or matches	0	0	0	0
The players of our team do not talk freely about the responsibilities that each player has in the game or in training	0	0.514	0.445	0
Eigenvalue	3.75	3.96	3.08	3.05
Variance Explained (%)	22.08	24.77	18.10	19.08
Reliability	0.799	0.834	0.743	0.706

BINARIZED COMPARISON – DIFFERENCES TESTS AND CORRELATIONS

	Social-related perceived cohesion	Task-related perceived cohesion
Sign test (p)	1.000	1.000
McNemar Test (p)	1.000	1.000
Cramer's V	0.514*	0.169
Contingency Coefficient	0.457*	0.167

Legend: *correlation significant at $p<.05$ level, two tailed
For the purpose of binarized comparison, all satisfying numerical component loadings (all except those with zeroes) are transformed in one ('1')

three principal components of perceived group cohesion (high personal standards, parental pressure and worry about mistakes), all tests of differences among two datasets (top basketball and recreational table tennis players) were insignificant. On the other hand, all the correlation coefficients indicated statistically significant and moderate positive correlations among two datasets in all three components of multidimensional perfectionism in sport situations.

This example reflects the fact that QCFA could reflect the differences/similarities in factor structures, at even bigger samples of entities (variables) in comparison, together with real existing differences/ similarities in factor structures. In this case, it can be concluded with even more certainty that similarities (together with the absence of differences) really exist among two datasets in all three components of multidimensional perfectionism in sport situations.

TABLE 4
DIFFERENCES AND CORRELATIONS AMONG COMPONENTS STRUCTURE OF MULTIDIMENSIONAL PERFECTIONISM IN SPORT SITUATIONS IN TWO DIFFERENT SAMPLES (BASKETBALL AND TABLE TENNIS PLAYERS)

Items	High standards		Parental pressure		Worry about mistakes	
	Basketball	Table tennis	Basketball	Table tennis	Basketball	Table tennis
If I do not set the highest standards for myself in my sport, I am likely to end up a second-rate player.	0	0.508	0	0	0.450	0.422
Even if I fail slightly in competition, for me, it is as bad as being a complete failure.	0.583	0	0	0	0	0.487
My parents set very high standards for me in my sport.	0	0	0.759	0.563	0	0
I feel like my coach criticizes me for doing things less than perfectly in competition	0.420	0	0	0	0	0
In competition, I never feel like I can quite meet my parents' expectations	0.458	0	0	0	0	0
I hate being less than the best at things in my sport	0.542	0.566				
If I fail in competition, I feel like a failure as a person	0	0.732	0	0	0	0
Only outstanding performance during competition is good enough in my family	0	0	0.534	0.625	0	
Only outstanding performance in competition is good enough for my coach	0.579	0.498	0	0.422	0	0
My parents have always had higher expectations for my future in sport than I have.	0	0	0.620	0.593	0	0
The fewer mistakes I make in competition, the more people will like me	0	0	0	0	0.662	0
It is important to me that I be thoroughly competent in everything I do in my sport.	0.434	0.677	0	0	0	0
I feel like I am criticized by my parents for doing things less than perfectly in competition.	0	0	0.593	0.573	0	0
I think I expect higher performance and greater results in my daily sport-training than most players.	0.595	0.736	0	0	0	0
I think I expect higher performance and greater results in my daily sport-training than most players	0	0	0	0.605	0	0
I feel that other players generally accept lower standards for themselves in sport than I do.	0.569	0.585	0	0	0	0
In competition, I never feel like I can quite live up to my parents' standards	0.451	0	0	0	0	0
My coach sets very high standards for me in competition.	0.668	0	0	0.419	0	0.486
If a team-mate or opponent (who plays a similar position to me) plays better than me during competition, then I feel like I failed to some degree.	0	0	0	0	0.600	0.737
My parents expect excellence from me in my sport	0	0	0.745	0.728	0	0
My coach expects excellence from me at all times: both in training and competition	0.415	0	0	0.593	0.483	0
If I do not play well all the time in competition, I feel that people will not respect me as an athlete.	0	0	0	0	0.655	0.620
I have extremely high goals for myself in my sport	0.461	0.721	0	0	0	0
I feel like my coach never tries to fully understand the mistakes I sometimes make	0	0	0	0	0.433	0.499
I set higher achievement goals than most athletes who play my sport	0.466	0.766	0	0	0	0
I feel like my parents never try to fully understand the mistakes I make in competition.	0	0	0.584	0.657	0	0
People will probably think less of me if I make mistakes in competition	0	0	0	0.567	0.655	0.491

TABLE 4 (continued)

Items	High standards		Parental pressure		Worry about mistakes	
	Basket-ball	Table tennis	Basket-ball	Table tennis	Basket-ball	Table tennis
My parents want me to be better than all other players who play my sport	0	0	0.483	0.651	0	0
If I play well but only make one obvious mistake in the entire game, I still feel disappointed with my performance	0	0	0	0	0.415	0.578
Eigenvalue	3.89	3.74	3.14	4.43	3.05	4.35
Variance Explained (%)	14.39	14.40	11.64	17.05	11.28	16.74
Reliability	0.751	0.838	0.757	0.808	0.741	0.824
BINARIZED COMPARISON – DIFFERENCES TESTS AND CORRELATIONS						
Sign test (p)	0.070		0.125		0.289	
McNemar Test (p)	0.070		0.125		0.289	
Cramer's V	0.472**		0.725**		0.431*	
Contingency Coefficient	0.427**		0.587**		0.396*	

Legend: *correlation significant at p<.05 level, two tailed; **correlation significant at p<.01 level, two tailed
For the purpose of binarized comparison, all satisfying numerical component loadings (all except those with zeroes) are transformed in one (1)

Conclusion and Extension

Simple robust method named Quasi-Confirmatory Factor Analysis (QCFA) has the purpose of comparing two factor structures, obtained by using exploratory factor analysis (EFA). The main advantages of QCFA are: simplicity of use and gaining exact indicators of similarities and differences among two datasets (factor structures in two different samples of entities). Comparing with other similar methods, QCFA deals not with first phase of EFA (when all variables are restrained in FA), but with the last phase (the best possible factor structure for certain dataset in EFA). The main shortcoming of QCFA is its robustness and the dependence on the number of variables that are compared in two datasets.

QCFA could have some possible extensions, in terms of its use for comparing two datasets of correlations with the same variable (e.g. set of nutritional contents with age in two data subsets: males and females). Using the same principle as in the case of comparing factor structures (calculating the differences and correlations), complete datasets of variables with their correlations could be compared. In the abovementioned example, it can be exactly concluded if two sets of correlations (for males and females) between age and nutritional contents are overall similar or different. The advantage of this method for comparing the whole sets of correlations is that there are no »blanks« that appeared from omitted variables during the phases of EFA, until achieving both interpretable and metrically satisfying final factor structure. However, this extension of QCFA has important limitations, linked with a nature of correlations and the relations about their statistical significance and height (lower values of correlations are statistically significant in larger samples). Hence, a very similar (or preferably the same) number of entities is the main prerequisite for such type of comparison. In other cases, individual comparisons of pairs of correlations using Fisher's Z-test are a better method for comparing two correlation datasets.

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JEDNOSTAVNA ROBUSTNA METODA ZA KVAZI-KONFIRMATORNU FAKTORSKU ANALIZU (TRI PRIMJERA)

S A Ž E T A K

U članku je predstavljena jednostavna robusna metoda nazvana Kvazi-Konfirmatorna Faktorska Analiza (KKFA, eng. QCFA), s ciljem usporedbe dvije faktorske strukture, dobivene prmjenom eksploratorne faktorske analize (EFA). Postupci EFA i CFA (konfirmatorne faktorske analize), zajedno s novim metodama koje se koriste u ovom području, često se koriste istovremeno u međukulturalnim istraživanjima za provjeru mogućnosti generalizacije uvezenih teorijskih konstrukata, na različitim uzorcima subjekata. U raspravi o tome »je li bolje koristiti EFA ili CFA?«, najtočnije je reći da je svaka od strategija prikladna u određenim istraživačkim situacijama. QCFA je konceptualno bliže EFA nego CFA, ali daje točne brojčane pokazatelje razlika, kaoi korelacija između dvaju faktorskih struktura, u završnoj fazi EFA. Pojedinosti o praktičnoj primjeni QCFA su prikazane u tri različita primjera. Raspravljene su prednosti i nedostaci ove metode, zajedno s njenom mogućom ekstenzijom.