EXPERIMENTAL COMPARATION OF GUTTMAN KAISER, PLUM BRANDY, SCREE AND PARALLEL ANALYSIS - MONTE CARLO CRITERIONS IN EXPLORATORY FACTOR ANALYSIS VIA SELECTED KINESIOLOGICAL RESEARCH

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Abstract
The aim of this study is to compare experimentally four different criteria for choosing number of principal components in exploratory factor analysis (EFA): Guttman-Kaiser (GK), Plum-Brandy (PB), Scree Plot (SP) and Parallel analysis - Monte Carlo (PAMC) via selected kinesiological research. Results clearly indicate that usage different extraction methods will, in general, give different number of latent dimensions. In accordance with obtained results, it is obvious that scientist or researcher in field of kinesiology have to be completely aware of advantages and problems in usage of each abovementioned FA extraction method criteria. Further researches of this type should be focused on analytical and experimental comparisons of results obtained by different criteria but on the sets of measured variables of well known latent structure.

Key words: *factor analysis, number of factors, criteria, comparison*

Introduction

Exploratory Factor Analysis (EFA) is advanced multivariate mathematical and statistical technique unavoidably used in kinesiology, sport sciences, psychology and in general social sciences (Viskić-Štalec, 1991; Borsboom, Mellenbergh & Van Heerden, 2003; Loehlin, 2003; Cudeck, & MacCallum, 2007; Marsh, 2007; Hox, & Roberts, 2010). As it is well known, factor analyses are performed by examining the pattern of correlations (or covariances) between the observed measures (Gorsuch, 1983; Mulaik, 1987). It is assumed that variables (measures) that are highly correlated (either positively or negatively) are probably influenced by the same underlying constructs or more precisely, latent dimensions or factors. On the other side, those variables that are relatively uncorrelated are likely influenced by different factors (Loehlin, 2003).

While using EFA, researchers hope that their results will extract what is called *simple structure*, with most items having a large correlations with one factor but small correlations on other factors (Comrey, 1978; Cudeck, & MacCallum, 2007). EFA is usually recommended when researchers have no undertheses about the nature of the underlying factor structure of their measurements. On the other side, when Confirmatory Factor Analysis (CFA) is being used, the researchers must specify the number of factors a priori (Loehlin, 2003; Kline, 2005; Marsh, 2007; Hox, & Roberts, 2010). EFA has three crucial decision points: first - choosing an extraction method, second - decide the number of factors to retain and third - choosing a rotation method (Ford, MacCallum, & Tait, 1986; Costello, & Osborne, 2005). In this article, focus will be on comparative analysis of decision how many factors to retain in selected kinesiological research.

During last decades, various authors have analyzed the importance of deciding how many factors to retain when applying EFA (Horn, 1965; Zwick & Velicer, 1986, Velicer, Eaton & Fava, 2000; Hox, & Roberts, 2010). Hayton et al. (2004) states three reasons why this decision is so important. Firstly, it can affect EFA results more than other decisions, such as selecting an extraction method or the factor rotation method, since there is evidence of the relative robustness of EFA with regards to these matters (Ford, MacCallum, & Tait, 1986; Zwick & Velicer, 1986). Secondly, the EFA requires that a balance be struck between "reducing" and adequately "representing" the correlations that exist in a group of variables; therefore her usefulness depends on distinguishing important factors from trivial ones (Ledesma, R. D., & Valero-Mora, 2007). Furthermore, various authors state that an error in terms of selecting the number of factors can significantly alter the solution and the interpretation of EFA results (Gorsuch, 1983; Wood, Tatryn, & Gorsuch, 1996; Cudeck, MacCallum, 2007; Ledesma, R. D., & Valero-Mora, 2007). Underextraction can lead to the loss of relevant information and a substantial distortion in the solution; for example, in the variables loading. On the other hand, overextraction although less grave, can lead to factors with few substantial loading, which can be difficult to interpret and/or replicate (Zwick & Velicer, 1986; Ledesma, R. D., & Valero-Mora, 2007). Same authors state, that, both underextraction and overextraction have consequences that adversely impact the EFA's efficiency and meaning. Costello and Osborne (2005) note that unfortunately, the most popular statistical programs do not provide users with the most accurate methods to solve a problem of number of factors to retain.

That is the most important decision to make after factor extraction. Mistakes at this stage, as it has been said before, such as extracting too few or too many factors, may lead to crucial misinterpretations in the analysis. Three criterions are most frequently used in sports sciences and kinesiology: Guttman-Kaiser criterion (GK), Cattell's Scree test, (Cattell, 1966) and Plum Brandy (PB) criterion (Štalec & Momirović, 1971). As a scientific result, PB criterion, unfortunately, was published only on Croatian language and is totally unknown outside of the borders of ex-Yugoslavia. Most commonly used criterion is GK which simply states that the number of factors to retain is equal to the number of factors with eigenvalues (explained variability) greater than variability of single manifest variable - 1.0. It is known, that eigenvalues are produced from a correlations by solving a characteristic equation

$$\det(\mathbf{R} - \lambda \mathbf{I}) = 0$$

or by a process called *Singular Value Decomposition* (SVD). Eigenvalues represent the variance accounted for by each underlying factor. It is well known fact that GK criterion has tendency of overfactorisation (Lužar, 1983, 1984; Wood, Tatryn, & Gorsuch, 1996, Wood, Tatryn, & Gorsuch, 1996) and GK is default criterion in commonly used statistical packages *Statistica* and *SPSS*. On the other side, the term "scree" is taken from the word for the rubble at the bottom of a mountain. SP is based on subjective analysis of scree plot - two dimensional visualization of correlation matrix eigenvalues trough graph with ordinal number (factor) on the x-axis and *eigenvalues* in descending order on the y-axis. From the scree plot, usually it can be seen that the first several factor account for most of the variance and the last factors are just "scree" or error variation. So, this approach to selecting the number of factors involves a certain amount of subjective judgment. According to PB criterion, significant are those components which explain "total multiple determination". Total amount of that variance is equal to sum of squared multiple correlations of each variable (criterion) with rest of variables (predictors). Researches point to the fact that PB criterion have tendency of hipofactorization and in that sense is opposite to GK criterion (Lužar, 1983, 1984). PB is not integrated in standard software packages as (default) option. Lastly, Parallel Analysis (PAMC) is a Monte Carlo simulation technique and provides a superior alternative to previously explained techniques (Hayton, Allen, & Scarpello, 2004; Ledesma, R. D., & Valero-Mora, 2007). As it is situation with PB criterion, PAMC is not well known among researchers, mostly because it is not included as an analysis option in the most popular statistical packages. Horn (1965) developed PAMC as a modification of Cattell's scree diagram to alleviate the component indeterminacy problem. The rationale is that sampling variability will produce eigenvalues > 1 even if all eigenvalues of a correlation matrix are exactly one and no large components exist (as with independent variates) (Zwick & Velicer 1986; Ledesma, R. D., & Valero-Mora, 2007). The eigenvalues from research data prior to rotation are compared with those from a random matrix (actually normal pseudorandom deviates) of identical dimensionality to the research data set (i.e. same number of *p* variables and *n* samples). Eigenvalues which are greater than their respective component EFA eigenvalues from the random data would be retained. Essentially, the parallel analysis works by creating a random dataset with the same numbers of observations and variables as the original data. A correlation matrix is computed from the randomly generated dataset and then eigenvalues of the correlation matrix are computed. When the eigenvalues from the random data are larger than the eigenvalues from correlation matrix you known that the components or factors are mostly random noise. Consequently, PAMC requires intensive computational process. Various studies indicate that PA is an appropriate method to determine the number of factors (Montanelli, & Humphreys, 1976; Zwick & Velicer, 1986). Also, Zwick & Velicer (1986) found that, among the methods analyzed, PA is the most accurate, showing the least variability and sensitivity to different factors. Furthermore, software that offers a PAMC as an option is not widely known among researchers. Today, there are some stand-alone programs for PAMC (Longman et al, 1989; Watkins, 2000) as well as some specialized macros for SPSS and SAS users (O'Connor, 2000). The aim of this study is to make experimental comparation of 4 different criteria for choosing number of principal components in EFA: GK, PB, SP and PAMC via selected kinesiological research.

Methods

The research was conducted on the sample of 238 pupils aged 10-12 years. The sample of variables used in this research were 4 standard anthropometric measures and 8 standard variables of motor status: body height (AVIS), body weight (ATEŽ), forearm circumference (AOP), upper arm skin fold (ANN), side steps (MKUS), polygon backwards (MPOL), standing on the bench (MP20), straddle forward bend (MPRR), hand-tapping (MTAP), long jump from a standstill (MSDM), sit-ups (MDTR) and held part in the hang (MVIS). All the measurements were done by qualified people who had big experience in collecting aforementioned data. By use *Statistica 8.0* software, eigenvalues of correlation matrix were calculated and number of principal components were calculated according to GK, SP and PB criterions. By use software (Watkins, 2000) Monte Carlo PAMC for parallel analysis was conducted. More precisely, Monte Carlo PCA for Parallel Analysis is a standalone Windows program that computes Parallel Analysis criteria by performing a Monte Carlo simulation. The user can specify 50-2500 subjects, 3-300 variables and 1-1000 replications. Program simuntaneously generates random normal numbers for the quantity of variables and subjects selected, computes the correlation matrix, performs Principal Components Analyses and calculates the eigenvalues for those variables, repeats the process as many times as specified in the replications field and calculates the average and standard deviation of the eigenvalues across all replications. For stable results, recommendation is to replicate at least 50-100 times (Watkins, 2000).

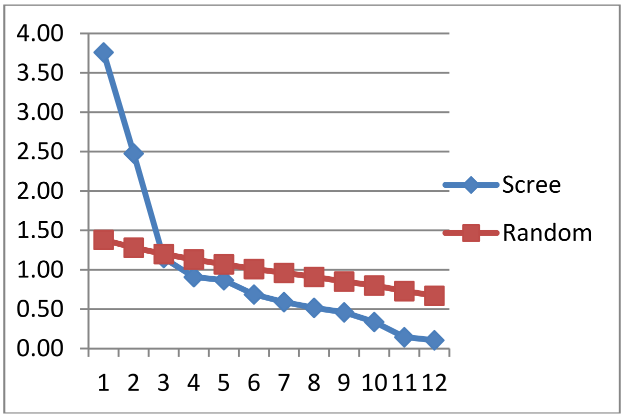
Results and discussion

Table 1. Eigenvalue of correlation matrix (Eignval), variability proportion of measured variables explained by single factor (%Var), cummulative eigenvalue (Cum.Eigv.), cumulative variability proportion of measured variables explained by single factor (Cum%)

	Eignval	%Var	Cum.Eigv.	Cum%
1.	3.76	31.33	3.76	31.33
2.	2.48	20.65	6.24	51.98
3.	1.15	9.58	7.39	61.56
4.	0.91	7.56	8.29	69.12
5.	0.87	7.23	9.16	76.34
6.	0.69	5.72	9.85	82.06
7.	0.59	4.92	10.44	86.98
8.	0.52	4.31	10.95	91.28
9.	0.46	3.83	11.41	95.11
10.	0.34	2.81	11.75	97.92
11.	0.14	1.20	11.89	99.12
12.	0.11	0.88	12.00	100.00

Table 1 shows eigenvalues of correlation matrix, absolute and cummulative variability proportion of measured variables accounted in for each factor. As it is shown in table 1, according to Guttman-Kaiser criterion three latent dimension have been extracted. Furthermore, as it can be seen on graph 1 and table 3, PAMC indicates that 2 latent dimensions exists.

As it can be seen from table 1 and table 2, according to the PB criteria, only one latent dimension is real. In table 3 results of PAMC analysis, by use of software (Watkins, 2000) are shown. Software was used for parameters: number of variables was set to 12, number of subjects was set to 238 and number of replications was set to 200.



Graph 1: Visualisation of correlation matrix eigenvalues - Scree Plot and visualisation of random eigenvalues - Parallel Analysis - Monte Carlo.

Table 2. Squred multiple correlations (SMC) of each variable with set of other variables.

	SMC
ATV	0.76
ATT	0.84
AOP	0.80
ANN	0.67
MKUS	0.23
MPOL	0.47
MP20	0.09
MPRR	0.17
MTAP	0.39
MSDM	0.52
MDTR	0.24
MVIS	0.30
Σ	5.49

Table 3. Parallel Analysis Monte Carlo results. Average eigenvalues of random correlation matrix (Rand.Eigenv) and their standard deviation (St. Dev.).

Eigenvalue#	Rand.Eigenv.	St. Dev
1	1.38	0.05
2	1.28	0.04
3	1.20	0.03
4	1.13	0.03
5	1.07	0.03
6	1.01	0.03
7	0.96	0.03
8	0.91	0.02
9	0.85	0.02
10	0.80	0.03
11	0.73	0.03
12	0.67	0.03

Probably, in this research, number of latent dimension should be 2 – morphological factor and general motor factor. In accordance with that only SP and PAMC showed real latent structure while PB and GK, as expected showed underfactorized and overfactorized latent structure, respectively.

Conclusion

When using exploratory factor analysis, it is of fundamental importance to precisely differentiate between methodologically problematic methods for determining the number of components to extract. As it is shown in this research, different methods that are standard used in scientific practice, on relatively simple variable sample give different number of extracted latent dimensions. GK criteria tends to overfactorization while PB criteria underfactorization while relatively good alternatives are SP and PAMC. Further scientific researches should include bigger samples of both cases and variables and give explicit recommendation for which criterion to use.

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EKSPERIMENTALNA USPOREDBA GUTTMAN-KAISEROVOG, PLUM BRANDY, SCREE I PARALELNE ANALIZE - MONTE CARLO KRITERIJA EKSPLORATIVNE FAKTORSKE ANALIZE KROZ ODABRANO KINEZIOLOŠKO ISTRAŽIVANJE

Sažetak

Cilj ovog rada je eksperimentalno usporediti četiri različita kriterija za odabir broj glavnih komponenti pri korištenju eksplorativne strategije faktorske analize (EFA): Guttman-Kaiser (GK), Šljivovica (PB), Scree plot (SP) i paralelnu analizu - Monte Carlo (PAMC) korištenjem odabranog kineziološkog istraživanja. Rezultati jasno pokazuju da će upotreba različitih metoda ekstrakcije, u pravilu, dati različit broj latentnih dimenzija. U skladu s dobivenim rezultatima, očito je da znanstvenici/istraživači u području kineziologije moraju biti potpuno svjesni prednosti i problema pri korištenju svakog od navedenih kriterija za odabir broja glavnih komponenata. Daljnja istraživanja ovog tipa trebaju biti usmjerena na analitičkim i eksperimentalnim usporedbama rezultata dobivenih različitim kriterijima, ali na skupovima manifestnih varijabli poznate latentne strukture.

***Ključne riječi**: faktorska analiza, broj faktora, kriteriji, usporedba*

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