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USING PARALLEL ANALYSIS TO VALIDATE THE CLANCE IMPOSTER PHENOMENON SCALE

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ABSTRACT
The most widely used instrument for identifying imposter syndrome is the Clance Imposter Phenomenon Scale (CIPS). Although the factor structure of CIPS has been checked in many research papers, using confirmatory factor analysis, so far no check has been made using parallel analysis. The aim of present study is to determine the factor structure of CIPS by applying parallel analysis. Both versions of the instrument have been tested, the 20-item version and the 16-item version. Parallel analysis, in this study, shows the justification of retaining a two-factor structure for the 20-item version or a one-factor solution for the 16-item version. In addition to being able to help determine the number of factors and components, parallel analysis in this case helped to come up with a solution proposal for decision about a version of the instrument that could measure imposter syndrome with a single score.

Keywords: imposter syndrome, CIPS, factor structure, parallel analysis.

1. INTRODUCTION

The term imposter syndrome was first used by Clance and Imes (1978) in seminal work about the imposter phenomenon, which phenomenon they described as an acquired emotional experience of inadequacy of achievement, acquired despite data and evidence that contradict this feeling. Individuals who show imposter feelings doubt their abilities, award deserve their success to external factors and feel that they do not deserve praise (Prata and Gietzen, 2007; Young, 2011). There are several main features of traditional definitions of imposter phenomenon: the feeling of an individual that he is a fraud, the fear that difficulties will be revealed, and the internalization of success (Leary, Patton, Orlando and Funk, 2000).

The most widely used instrument for identifying imposter syndrome is the Clance Imposter Phenomenon Scale (CIPS) (Clance, 1985). The instrument was constructed by Clance, as a scale of 20 items that should examine traits associated with imposter syndrome such as fear of evaluation, fear of not being able to repeat success, and fear of an individual being less capable than others (Chrisman, Pieper, Clance, Holland and Glickauf-Hughes, 1995). Each item was scored on a five-point scale, from 1 (not at all true) to 5 (very true). A scale has been developed to identify whether individuals have a fear of failure, a fear of appraisal, a complacent acknowledgment from others, and a fear that they may not be able to replicate previous success (Langford and Clance, 1993).
An initial exploratory factor analysis of Clance Imposter Phenomenon Scale (Chrisman et al., 1995) found that the instrument includes three dimensions (fake, discount and luck). In recent

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research (Brauer and Wolf, 2016), three factors have also been identified. Despite the fact that explanatory factor analysis indicates a three-factor structure, the researchers subsequently tested this solution by confirmatory factor analysis on a one-factor, two-factor, and three-factor model (Brauer and Wolf, 2016; French, Ulrich-French and Follman, 2008; Jostl, Bergs, Bergten, Bergs Schober and Spiel, 2012).

In the first study by confirmatory factor analysis, but on a 16-item version, authors found that the two-factor model best explains the structure of the instrument (French et al., 2008). The 16-item version was selected based on research (Kertay, Clence and Holland, 1991), in which items 1, 2, 19 and 20 were excluded from the proposed set of items (based on law discrimination, factor saturation, communalities and inter-items statistics)(Kartey, 1992). Jostl and associates proposed a one-factor solution for which he found better goodnes of fit results (Jostl et al., 2012). In the 16-item version, in the verification of the three-factor solution, it was found that this solution (one factor) fits better than other solutions (Brauer and Wolf, 2016). Finally, in a confirmatory factor analysis, on a sample of doctoral candidates (Simon and Choi, 2018), based on model indicators and residual correlation levels, it was concluded that the one-factor model (for 20 scale items) best explains the factor structure of CIPS (factor loadings from 0.48 to 0.82, Cronbach’s $\alpha = 0.85$).

Based on this, it could be concluded that conflicting results of factor checks were obtained. Also, it is not entirely clear why the authors opted for a longer or shorter version of the scale. This is especially because it has been determined that individual items measure similar aspects of the construct (Jostl et al., 2012). Nevertheless, previous research has shown that this scale reliably distinguishes imposters from non-imposters (Holmes, Kertay, Adamson, Holland and Clance, 1993).

In a systematic review based on a meta-analysis of research papers in which the factor structure of the CIPS scale was checked (Mak, Kleitman & Abbot, 2019) but also on the basis of a review of the database, we did not find any research paper using parallel analysis as a method for determining the number of factors and components of imposter syndrome. Given the robustness of the range and the potential of parallel analysis, it is not entirely clear why the researchers did not use it. One possible answer is computational complexity (demanding syntax).

Parallel analysis (Horn, 1965) is a procedure based on the assumption that only those dimensions whose characteristic roots are larger than the characteristic roots that can be obtained on the basis of random data with analogous characteristics (eg. the same number of variables and cases) should be retained. Parallel analysis, therefore, takes into account the variability resulting from the specificity of sampling and can be seen as a modification or correction of the K1 rule, as it provides an exact starting point for eliminating dimensions whose variance is not greater than would be expected for random data (where no "real" dimensions exist).

Simulations demonstrate that parallel analysis is the most accurate existing method for determining the number of dimensions in principal component analysis (Zwick and Velicer, 1986) with a success rate of about 84% in lower saturation conditions, up to 99% in higher saturation conditions. When it errs, parallel analysis generally overestimates the number of dimensions (65% of errors are overestimations). Horn (Horn, 1965) parallel analysis (despite conceptual differences), int this study, is very precise in determining the number of factors - e.g.

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Lorenzo-Seva et al. (Lorenzo-Seva, Timmerman and Kiers, 2011) obtain an overall success rate of 81%.
Parallel analysis is probably the best existing procedure for estimating the number of dimensions (Timmerman and Lorenzo-Seva, 2011; Zwick and Velicer, 1986) and at this time it is difficult to find convincing arguments against its use as a default procedure (excluding PA-PAF to be avoided) and PCA and EFA. In addition, parallel analysis seems to tend to ignore minor factors (Timmerman and Lorenzo-Seva, 2011), ie. factors that explain the trivial percentages of variance and are mostly a manifestation of empirically "insignificant" relations, such as similarities in the linguistic formulation of the item.
So, having all this in mind, the aim of present study is to determine the factor structure of CIPS by applying parallel analysis.

2. METHOD AND MATERIALS

The aim of the research. The aim of the present study is to determine the factor structure of CIPS by applying parallel analysis.

Research question. Our research question is whether by using parallel analysis, on a selected sample of second-career teachers and on the instrument for measuring the imposter phenomenon, a result can be obtained that could contribute to resolving the dilemma about the dimensionality of imposterism?

The hypothesis we started from was that, despite the fact that it almost does not appear in the research literature for determining the number of factors, the parallel analysis of CIPS can help around the mentioned dilemma of multidimensionality or unidimensionality.

Participants. The 91 second-career primary school teachers in the sample (N=91, M= 140,32, SD= 13,632) consisted of 38,3% male and 64,7% female teachers, with 55% of 10 and below years of professional expiriences and 65% of excellent and moderate academic achivement. A two-way factorial ANOVA revealed that there were no significant differences between genders and expiriences on the total CIPS scores. We used the selected sample of second-career teachers because we started from the assumption that it is easier and more visible to find imposterism on a sample of adult respondents who changed professions.

Procedure. Respondents were given questionnaires in schools, after being explained the purpose and goal of the research. Ethical issues were explained and formal consent was obtained to participate in the research.

Measures. Two versions of the instrument were used, a complete version consist of 20 items (Clance, 1985) and an short version consist of 16 items (Kertay, 1991; Chrisman et al. 1995). In the second version, items 1, 2, 19 and 20 were omitted. SPSS 17.0 was used for statistical processing and a defined version of rawpar.spss syntax was used for parallel analysis (O'Connor, 2000).

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3. RESULTS AND DISCUSSION

The Kolmogorov-Smirnov normality test for the whole scale indicates a deviation from the normal distribution (Z = 2,759, M = 83,16, Sd = 5,78, p = 0,000). We assume that the reason is the heterogenity of the specific group of teachers surveyed (second-career teachers and different professional and personal backgrounds). The Cronbach's alpha reliability coefficient for 20 scale items (CIPS-20) is $\alpha = 0.81$, and for the shorter scale version (CIPS-16) of 16 items $\alpha = 0.82$.

Parallel analysis for CIPS-20. The results of the parallel analysis, for the first version of the scale, indicate the justification of accepting two factors. The characteristic values of the two components exceed the corresponding threshold values obtained using an equally large matrix of random numbers (Table 1). The obtained correlation between these two factors r = 0.38.

Table 1. Comparison of characteristic values obtained in PCA and threshold values obtained by parallel analysis for CIPS-20.

Ordinal number of the component	Generated characteristic value from PCA	Value obtained by parallel analysis	Decision
1	5,558701	4,676457	accept
2	3,937761	3,694111	accept
3	2,992712	3,066966	reject
4	1,797947	2,563960	reject
5	1,653588	2,151923	reject
6	1,000743	1,792487	reject
7 […]	,937760	1,489564	reject

Parallel analysis for CIPS-16. The results of the parallel analysis, for the second version of the scale, indicate the justification of accepting one factor. The characteristic values of that one component exceed the corresponding threshold values obtained using an equally large matrix of random numbers (Table 2).

Table 2. Comparison of characteristic values obtained in PCA and threshold values obtained by parallel analysis for CIPS-16.

Ordinal number of the component	Generated characteristic value from PCA	Value obtained by parallel analysis	Decision
1	5,154400	4,128106	accept
2	3,007823	3,203049	reject
3	2,498069	2,587911	reject
4	1,380843	2,146471	reject
5	1,187297	1,751677	reject
6	,935854	1,441112	reject

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7 […]	,678449	1,156908	reject

A significantly larger number of published papers and conducted research, in which the number of components on CIPS is determined through confirmatory factor analysis than those that use different methods from CFA to determine the number of components, complicates the discussion on this topic. What can be compared are the results of the confirmatory factor analysis from the research in which the factor structure of CIPS is determined and the results of the parallel analysis from our research.

For the version of the 20-item scale, for which we obtained two factors in the parallel analysis, only one study appears in the literature (Leonhardt, Bechtoldt and Rohrmann, 2017) in which the authors identified two components. It is about agglomerative cluster analysis with the Ward procedure to distinguish between groups who experience imposterism, for obtained 2 clusters. Similarly, sample consisted of 13 employees in leading positions. In all other studies, a one-factor or three-factor scale structure was obtained.

For the 16-item scale version, we found two surveys that are in line with our results. In the research of French et al. (2008), it was obtained: CFA with RWLS estimation, for Model 1 with 3 factors (theoretically preferred - Fake, Discount and Luck) and Model 2 with 2 factors (best fit obtained). Also, for the 16-item version, Jostl et al., 2012 CFA of German CIPS was done and then path modeling for several related regression relationships - replicated Chrisman et al., 1995 - 3 factors model with poor fit. Single factor model of CIP better fit.

It has been discussed in the literature whether the multidimensional factor structure fits better than the unidimensional model. Thus, the multidimensionality of the CIPS scale is critical. In checking multidimensionality, the high correlations of factors obtained made it difficult to identify “core feelings of inauthenticity that are central to imposterism” (Leary et al., 2000: 735).

In recent research, it is as if the same pattern is being perpetuated in the dimensionality test: multidimensionality is disputed, but when a conclusion is reached about unidimensionality - researchers retreat to the position of justification of a three-factor or at least bi-factor model. Therefore, we believe that the results of our analysis can help resolve the dilemma and dispute.

For such a completely vague picture and inconsistency of data in the factor determination of imposterism, we assume that the reason is the complexity of the phenomenon we are examining, its diffuse and elusive nature that eludes sizing. However, we have to ask ourselves whether the scale can measure the imposter phenomenon with one score. Our results indicate that for this purpose, it is better to use an abbreviated version of the 16-items scale to measure this phenomenon over a single scale. Taking into account the obtained coefficients of reliability and the fact that they differ minimally for the first and second versions of the scale ($\alpha = 0.82$, $\alpha = 0.81$), this previously stated statement was fully justified.

It would be correct to emphasize that the use of parallel analysis to determine the definite number of factors is closely related to all other methods for model definition. We believe that it can find its place in solving the problem of prefactoring and subfactoring. Although the author's preference is on the side of confirmatory factor analysis, and the use of the principle of calculating covariances in the standard solution model, the capacities and all the potentials of parallel analysis cannot be given up.

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