Common Factor Analysis and Component Analysis: Are They Interchangeable? A Word of Caution

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ABSTRACT

In this review, we revisit the debate over the interchangeability of the statistical techniques of common factor analysis and component analysis. The literature shows that both techniques are conceptually distinctive. Additionally, the position that component analysis, in practice, can be used as an effective substitute for common factor analysis has provided mixed results. This paper discusses the risk of mixing up these techniques and concludes with some recommendations for this issue.

Keywords: Factor analysis, principal component analysis

For a long time, factor analysis techniques have been widely used in almost every social science discipline as these techniques provide researchers with powerful capabilities to manage huge data sets to achieve various objectives. Factor analysis has significantly contributed to the advancement to research and it has been mainly utilised for the purposes of examining patterns of interrelationship, data reduction, classification and description of data, data transformation, and hypothesis testing (Ford, Maccallum & Tait 1986; Loehlin 2004). Moreover, researchers have commonly used exploratory factor analysis as a technique to develop scales (Gorsuch 1997). Exploratory factor analysis is considered to be the most studied and used latent variable method in the social and behavioural sciences (Pruzek 2005).

Common factor analysis and component analysis have occupied a prominent position within current published research. Although each of these techniques has specific potential, common factor analysis and component analysis, in particular principal component analysis 'PCA', which is considered to be the most widely used type of component analysis (Widaman 1993; Velicer & Jackson 1990b), have been used interchangeably based on some research results that reported the similarity of the outcomes of these two statistical techniques. In this paper, we try to highlight the contradictory points of view and empirical results regarding this issue, in an attempt to give guidance to researchers when they are faced with such a choice. Specifically, we focus on the decision of choosing the extraction model or method of analysis (i.e. common factor analysis or component analysis). This decision has been hotly debated (Henson & Roberts 2006) and may have critical consequences and that is why some factor-analytic theorists argued that this issue can be seen as the most important decision of all (Goldberg & Velicer 2006). There are some topics that need to be discussed in order for us to gain an insight into this topic. These include the theoretical differences between the two competitive techniques and the different points of view regarding this practice of interchangeability. Also, it is important to have a look at the current practices of researchers in the light of the results and recommendations of the extant literature.

THEORETICAL DIFFERENCES BETWEEN COMMON FACTOR ANALYSIS AND COMPONENT ANALYSIS

Differentiating between PCA and common factor analysis, Fabrigar, Wegener, MacCallum and Strahan (1999) contended that PCA mainly aims to achieve date reduction. That is, to find a number of factors that are able to represent the original data set and make it easier to express. Whereas, the main purpose of common factor analysis is to identify latent constructs. In other words, common factor analysis seeks to arrive at a parsimonious representation of the associations among measured variables. The use of PCA helps a researcher to discover the maximum variance among the observed variables but common factor analysis is more appropriate when the researcher supposes that these observed variables represent a linear function of a set of unmeasured or latent variables (Ford et al. 1986).

This distinction is important especially when we know that data reduction does not attempt to model the structure of correlations among the original variables. Ford et al. (1986) further explained that although both common factor analysis and PCA have the ability to examine the variance of a particular variable relative to the variances of other variables, common factor analysis has the merit of distinguishing between common variance (the covariance between variables) and unique variance (random error variance and systematic variance specific to a particular variable). This means that common factor analysis provides valuable insights into the multivariate structure of a measuring instrument and has the ability to isolate the constructs whose effects are reflected in responses on the instrument (Floyd & Widaman 1995). Snook and Gorsuch (1989) proposed that PCA reflects a mathematical paradigm, whereas common factor analysis follows a statistical paradigm. That is, common factor analysis presumes that there should be an error as a result of extracting factors representing the variance of observed variables (manifest variables may be fallible). On the contrary, PCA is based on the assumption that there is no such error. In other words, PCA implies that the correlation matrix of the sample perfectly reflects the population correlation matrix. Here, we adopt a statement form (Loehlin 1990: 30), who said that 'if one lives in a real world in which measures contain error and/or specific variance, why not fit models that reflect this'. Moreover, some researchers argued that component analysis is considered a special case of common factor analysis through the supposition that there is no error term. Therefore, if component analysis is appropriate, common factor analysis is also suitable, but the reverse is not correct (Gorsuch 1990; Gorsuch 1997).

Gorsuch (1997) contended that as component analysis assumes that there are perfect correlations between variables and factors, it does not include an error term when constructing component equations that seek to maximise the multiple correlations of component to items, whereas the common factor analysis does. To interpret the observed variables as manifestations of unitary underlying entities or to find the pattern of covariation among a set of variables, common factor analysis seeks to minimise the effects of common error, specific variance on the common factor pattern loadings and intercorrelations among factors (Widaman 1993).

As the main goal of item analysis is to select variables that are most related to the construct, Gorsuch (1997) argued that common factor analysis is more appropriate for item analysis because the 'perfect reproduction' assumption PCA holds, requires that variables are almost reliable and correlate highly with at least one other variable and this is not always the case. Therefore, including the error term, which is applied by common factor analysis, is more convincing. Consequently, as most study measures are believed to have errors, common factor analysis is a more realistic model of the correlations of measured variables (Fabrigar et al. 1999).

More importantly, common factor analysis deals with factors as the causes of the observed variables, whereas PCA represents the variances of the observed variables as an economical way of expressing these variables and no latent variables underlying these observed variables are claimed. These principal components are weighted sums of the observed variables. Therefore, the observed variables, contrary to common factor analysis, may be thought of as the causes of the composite variables (Floyd & Widaman 1995).

Drawing on the above, many researchers consider that PCA is not a type of factor analysis at all (Preacher & MacCallum 2003; Henson & Roberts 2006). For example, Cudeck (2000) thought that not only PCA is often incorrectly used as a kind of factor analysis but also many published articles erroneously presented PCA results as a variety of factor analysis and he contended that PCA is mainly a technique for summarizing the information contained in several variables into a small number of weighted composites. Also, Fabrigar et al. (1999) posited that many researchers mistakenly believe that PCA is a type of exploratory factor analysis when these two tools are different techniques with different objectives. Moreover, Mulaik (1990) argued that using component variables in generalizations to other sets of variables (as the factor common to them) is awkward, if not impossible.

However, many methodologists and researchers think that although there are theoretical and conceptual differences between the two statistical techniques, these differences are not important if the empirical results of these two techniques provide convergent solutions (Snook & Gorsuch 1989).

IS COMPONENT ANALYSIS EFFECTIVE ENOUGH?

Floyd and Widaman (1995) claimed that despite the common use of factor analysis, both complexity and flexibility of factor analytic procedures are responsible for ambiguity about the appropriate practices and, in turn, may lead to some inconsistencies in results across studies and also controversy over substantive research issues.

Some researchers rely on the notion that the results of both PCA and common factor analysis are so similar that they justify using them interchangeably (Goldberg & Velicer 2006). However this point of view is not accepted by other researchers who think that these numerical coincidences are not guaranteed and therefore this claim cannot be generalised (Cudeck 2000).Therefore, this section deals with the rationale used by both proponents and opponents of this interchangeability practice.

Proponents of the Interchangeability between the Two Techniques

Although most writers think that common factor analysis is the preferred procedure, component analysis has been the most widely applied technique (Velicer & Jackson 1990b). In practice, many researchers interpret the results of PCA as approximations to common factor analysis. This position mainly relies on some empirical studies that showed that this rule of approximation between the two tools is appropriate as long as there are great number of variables (e.g. not less than 30) in the study and high communalities (e.g. greater than.40) among variables (Floyd & Widaman 1995; Fabrigar et al. 1999). For example, the Monte Carlo study of Velicer, Peacock and Jackson (1982), that tried to compare the results obtained by maximum likelihood, PCA, and image component analysis, showed no significant differences between all these three techniques. Velicer and Jackson (1984), through their review of the literature that compared common factor analysis and PCA, indicated that there was no distinction between these two tools at the empirical level (cited in Snook & Gorsuch 1989).

At the mathematical level, PCA and common factor analysis look at the communality of measured variables differently. PCA utilises a correlation matrix among measured variables with 1.0’s on the main diagonal whereas common factor analysis utilises a correlation matrix with communality estimates on the main diagonal. Simply, that means that PCA tries to represent all the variance of the observed variables, but the common factor analysis tries to find only the common variance of each variable (Floyd & Widaman 1995). The higher the reliability score of a variable is, the closer the common factor analysis entry on the diagonal is to unity. Therefore, when the reliability of variable scores is high, PCA and common factor analysis will converge in their estimates (Thompson & Vidal-Brown 2001).

Some methodologists justified why the estimated results of both techniques converge as the total number of variables increase. They argued that the proportion of the entries on the diagonal decreases exponentially as the total number of measured variables increase. For example, if we have 10 variables, there are 10 diagonal entries out of 100 total entries (10%), and if we have 30 variables, there are 30 diagonal entries out of 900 total entries (3.3%). That means that the impact of the diagonal entries decreases with the increase of the measured variables and, in turn, the difference in the estimation of the two methods shrinks (Thompson & Vidal-Brown 2001; Loehlin 2004; Goldberg & Velicer 2006). Thompson and Vidal-Brown (2001) also empirically supported this position and found that the magnitude of the absolute values of the loading coefficients converged for both techniques with a data set from 539 college students on the career assessment diagnostic inventory (CADI).

Having followed a similar line of thought, other researchers adopted the notion that it is the number of variables per factor, and not the total number of variables, that determine the degree of similarity between these two analyses. Accordingly, the grater variables per factor (e.g. more than three indicators; Fabrigar et al. 1999) and the communality level are, the more similar are the results between common factor analysis and PCA. Velicer and Jackson (1990a; 1990b) posited that the greatest discrepancies in results between the two techniques are expected when the ratio of variables per factor is very small and the loading of manifest variables on factor is very low and argued that there is little basis to prefer any of these two competitive techniques. Accordingly, they thought that other decision such as the number of factors/component to retain or rotation method, are more important for researchers.

Opponents of the Interchangeability between the Two Techniques

On the other hand, Widaman (1993) stated that there has been no complete consensus on the conclusions that Velicer and Jackson arrived. In other words, Widaman (1993) claimed that most of the comments following their account called for some qualifications for these conclusions. For example, Mulaik (1990) criticised Velicer and Jackson implications and stated that they cited results charcterised by variables with high loadings (all were equal to .80), which may be not a very good test case. He asked the question, 'What would happen if all non-zero factor pattern loadings of the common factor model were .30 or .20?' Additionally, Velicer and Jackson did not cite other two studies that had reported strong differences in results from PCA and common factor analysis.

It is noteworthy that because the component loading involves both the common and unique variance, PCA was found to be giving higher loadings than common factor analysis (Velicer et al. 1982). Accordingly, in the Monte Carlo study of Snook and Gorsuch (1989), contrary to the results of PCA which showed inflated loadings, common factor analysis showed unbiased results even in the samples where it was expected that both common factor analysis and PCA would converge due to the large sample size and increase of communality value. Also, they argued that this bias in component loadings was negatively related to both the total number of observed variables in the analysis and to the level of communality. Moreover, they argued that these inflated loadings (though misleading) make it easier for a researcher to interpret data, and that, in turn, may be a reason why PCA is more popular in applied research.

Preacher and MacCallum (2003) demonstrated empirically that there was a simple structure in the common factor analysis results, compared to PCA. These loadings in the factor solution were quite consistently and often substantially smaller than the corresponding loadings in the component solution. This simple and consistent structure suggests more precise definition of the constructs in the factor solution than in the component solution.

More importantly, many applications that require exploratory factor analysis are related to item-level data, which is often characterised by low communalities. If a few of these items loaded on specific factors that, in turn, would lead to significant differences between the results of the two tools. Therefore, common factor analysis is the appropriate option as it is able to arrive at accurate estimates of factor loadings and factor correlations (Floyd & Widaman 1995). Moreover, Widaman (1993) conducted an empirical study to test the claim that common factor analysis and PCA techniques are similar in their results and he concluded that PCA should not be used if the aim of the researchers is to extract parameters reflecting latent constructs.

Because factor analysis explicitly deals with unique variance, Widaman (1993) argued that it is not uncommon to have cases in which common factor analysis explains from 30 to 50, and sometimes less, percent of the total variance of measured variables. Therefore, researchers who seek to use PCA as an interchangeable tool for common factor analysis should justify that PCA approximately represents these factors that would be extracted by common factor analysis. Widaman (1993) also argued against the practices of most statistical packages that use PCA as their default. He insisted that the results of his study showed that the parameters defined by both techniques differed systematically even when the correct number of dimensions are retained and any in many cases these differences are nontrivial. Widaman (1993) concluded that, given the data nature investigated in social and psychological sconces, we rarely find a prudent researcher who opts for PCA when his or her goal is to interpret patterns of observed covariation among variables.

Gorsuch (1997) argued that there may be four reasons that PCA is preferred to common factor analysis. These are (1) common factor analysis has a technical problem as there is no unique set of factor scores that can be calculated from it compared to PCA. Thompson & Vidal-Brown (2001) thought that this is considered to be a unique feature of PCA as researchers may use these factor scores in subsequent analyses such as MANOVA, descriptive discriminant analysis. However, some applications such as item analysis is not affected much of this as item analysis seeks subset of items to score each factor and that represents a unique set of factor scores for common factor analysis. Additionally, this indeterminacy of individual factor scores in the common factor model usually does not represent a real problem as researchers may use structural equation modeling and use these factors as predictors, correlates, or consequences of other variables without estimating factor scores or they may use alternative nonstructural methods to find the correlations between factors and other variables without the need to calculate factor scores (Fabrigar et al. 1999; Gorsuch 1997). (2) PCA is easier to compute. However, this position is somewhat redundant due to massive advances in personal computers and their huge mathematical capacities. (3) The commonly used procedure of maximum likelihood with highly iterated communalities, which is often used with common factor analysis, shows occasional problems. Also, this cannot be considered a serious point because this problem does not appear when using principal axis common factor analysis. (4) Researchers think that there are similarities in results obtained using any of these techniques. Once again, this hypothesised position cannot be achieved unless there are high correlations among the set of variables or there is a large number of variables per factor, which may be seen as contextual (Fabrigar et al. 1999).

Due to the 'Heywood cases', which means having a communality of or greater than unity for a measured variable, some methodologists argued that PCA is considered a substitute for common factor analysis and might even be superior (Fabrigar et al. 1999). However, opponents argued that Heywood cases can be seen as a diagnostic tool. That is, it represents an indicator of a data violation of the common method analysis assumptions or it indicates that a misplaced model has been fit to the data. In contrast, this feature is absent when using PCA because these possible problems are unseen.

CURRENT PRACTICES FOR CHOOSING FACTOR EXTRACTION MODEL

Although the literature has included some important contributions that attempted to raise the quality of decisions related to exploratory factor analysis practices, it seems that these efforts have had rather little impact on methodological choices made (Preacher & MacCallum 2003).

Floyd and Widaman (1995) thought that researchers should justify their use of particular options of factor analysis, such as the technique used, factors to retain, rotation method, according to some standards, and that they should give sufficient detail about these chosen decisions to help the interpretation of results obtained by them.

Despite the hot debate over the possibility of using PCA as an effective substitute for common factor analysis in order to get benefits from its claimed features, both theory and empirical evidence have favoured common factor analysis as the more appropriate procedure (Conway & Huffcutt 2003).

A thorough look at the current practices related to exploratory factor analysis indicates that researchers usually use component factor analysis as a substitute for common factor analysis to determine factor structures among manifest variables. More importantly, this choice is most often taken as a routine decision despite the 'not convincing enough' evidence in the literature.
Examples of questionable decisions, including the chosen extraction model, are still common in the literature (Conway & Huffcutt 2003; Preacher & MacCallum 2003). Preacher and MacCallum (2003) stated that many published works followed the 'Little Jiffy' approach, including favouring the PCA over common factor analysis, in whole or in part. Having reviewed exploratory factor analysis practices in organisational studies in three journals from 1985 to 1999, Conway and Huffcutt (2003) found that PCA was the most popular factor extraction model. In this study, they found that 124 studies reported using PCA, 72 studies used common factor analysis, and 93 studies reported no information about the factor extraction model used. We argue that the large number in the last category may imply that many researchers think that it makes no difference to choose between any of these two models, as reflected in authors' neglect to provide this piece of information. Moreover, these results were generally consistent with the review results by both Ford et al. (1986) and Fabrigar et al. (1999) which showed that PCA is more used in published works.

Recently, there have been many studies that can be characterised by questionable practices regarding choosing the factor extraction model. For example, in her study of organisational values and commitment, Finegan (2000) used PCA to group measured values into higher order variables to create scales for values. She justified her choice based on the results that supported the similarity of results between common factor analysis and PCA. Moreover, she gave this section of the study the title ‘principal component factor analysis’, which implied that this technique is theoretically and empirically a type of factor analysis. Moreover, Abbott, White and Charles (2005) extended the previous study and followed the procedure of PCA to group their measured values and they also interpreted the resulted three clusters of values as ‘factors’. These actions may be questionable because from a conceptual perspective, the literature has supported the distinction between the two statistical techniques. Additionally, although the literature showed that the similarity of results between these two competitive techniques depended mainly on contextual evidence and that the extant empirical literature generally yielded no clear results, the two motioned studies did not provide enough information that justified their decisions.

As a practical example of the mixed results obtained from the two techniques, Prins (2006) was not able to replicate the five-factor emotional intelligence structure as proposed by (Palmer & Stough (2001) in Prins (2006)). The author suggested that the inconsistent results could have arisen because of sample differences. However, another possible explanation she suggested was that Palmer & Stough applied the PCA, utilising varimax rotation while she used principal axis factoring and direct oblimin rotation, which constitutes a more rigorous test than the former methodology. Principal axis factoring (common factor analysis) usually leads to fewer factors than would be found with the PCA. It is noteworthy that these inconsistent results also occurred when she examined the psychological climate construct as proposed by (Brown & Leigh (1996) in Prins (2006)). However, this study was able to replicate the two job affect dimensions as proposed by (Brief et al., (1988) in Prins (2006)) and the three-factor burnout structure as proposed by (Maslach & Jackson (1986) in Prins (2006)), albeit with different factor loadings on the individual items.

SUMMARY AND CONCLUSION

The literature reviewed supports the conceptual and theoretical distinction between the statistical techniques of component analysis and common factor analysis. On the other hand, the empirical studies that compared the similarity of the results of both techniques have provided mixed results.

It may be noteworthy that, given the available results and the complexity of such techniques and their applications, we think that many other empirical studies are still required to help researchers make a more informed decision regarding this choice.

Although theory and results, to date, have generally tended to prefer common factor analysis over component analysis when dealing with latent structure issues, researchers often have used component analysis instead. Because the results that may support the similarity of results between the two techniques can be described as contextual or circumstantial, we argue that it is safer to avoid this practice of interchangeability or at least to exercise great caution in using component analysis as an alternative to common factor analysis. Misuse of exploratory techniques may cause misleading or at least inaccurate or distorted results, which may be reflected in the level of the reliability of empirical studies.

We urge researchers to adhere to common factor analysis for identifying latent constructs and to use component analysis for data reduction goals. Because the results that may support the similarity of the outcomes of these two techniques are not decisive or convincing enough, it would be a good practice for those who advocate using component analysis as an effective substitute for common factor analysis, to report the results of the two techniques or at least to clearly justify the rationale behind preferring component analysis over common factor analysis. Based on the previous recommendation, the practice of reporting the results of the two techniques would have twofold contributions to the field: (1) to make more comparisons of the accuracy of the results, which would give us more insight into this research point through using wider real data sets, and (2) to make component analysis results more reliable for use in sequential analyses. More importantly, strictly pursuing common factor analysis or following the procedure of reporting the results of the two statistical techniques would raise the quality of exploratory factor analysis results through increasing the validity of scales derived from factor analysis-based studies.

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