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Exploratory Factor Analysis and Principal Component Analysis in Clinical Studies: Which one should you use?

Introduction

Factor analysis covers a range of multivariate methods used to explain how underlying factors influence a set of observed variables. When research aims to identify these underlying factors, exploratory factor analysis (EFA) is used. In contrast, when the aim is to test whether a set of observed variables influences responses in accordance with an existing conceptual basis, confirmatory factor analysis is performed. EFA has many similarities with a commonly used data reduction technique called principal component analysis (PCA). These similarities along with using the related terms *factor* and *component* interchangeably, contribute to confusion in analysis. The difficulty in identifying the appropriate use of statistical methods, and their application and interpretation, impacts clinical and research implications (Beavers, Lounsbury, Richards, Huck, Skolits & Esquivel, 2013; Tabachnick & Fidell, 2001). We acknowledge previous articles in nursing journals offering guidance on the use of factor analysis (Gaskin & Happell, 2014; Watson & Thompson, 2006).

EFA and PCA are commonly used techniques to express multivariate data with fewer dimensions. The aim of these techniques is to summarize a set of original variables into a smaller set of factors or components that maximize the possible information and variation from the data in the original variables (Meyers, Gamst, & Guarino, 2013). EFA focuses on interrelationships between variables, and hence covariance is used to identify factors, while PCA uses the variance to identify components. In this editorial we identify some essential methodological considerations that must be taken into account when using these techniques, and compare their application using the examples of “hospitalization stress” and “hospitalization related stressors”.

2. Principles of EFA and PCA

Exploratory factor analysis is a statistical technique used to simplify complex data sets by examining the pattern of correlations (or covariances) among observed variables (Kline, 1994). EFA is particularly useful in investigating complex concepts which are not easily measurable such as mental health and quality of life. EFA includes the concept of a *latent factor* that exerts influence on observed variables (Basto & Pereira, 2012). The aim is to concisely represent interrelationships to aid conceptualization of a set of latent constructs underlying a battery of measured variables. The information from the original measured variables is presented in a smaller number of derived factors (Gorsuch, 2014). The key objective is to extract the maximum common variance from the variables to arrange them under common factors to understand how much each variable contributes to each factor. The proportion of variance which can be explained by a set of factors which are common to the other observed variables is called *communality*. The degree of communality provides information to decide whether a particular factor should be retained. There is also a unique variance to that variable, known as *uniqueness*, and a proportion of the variance not explained by the factors, the error variance.

PCA is used to simplify complex data by identifying a small number of *principal components* which capture the maximum variance. These components are linear combinations of the original variables. PCA and EFA achieve data simplification by identifying the number of components and factors respectively which explain the set of observed variables (*Component*/*Factor retention*). This choice involves a trade-off between parsimony (retaining fewer components/factors) and completeness (explaining more variance). Some other applications of EFA, in addition to data reduction, are analysis of multiple indicators, measurement and validation of complex constructs, development and/or assessment of psychometric properties of new scales (Boateng, Neilands, Frongillo, Melgar-Quiñonez, & Young, 2018; Gorsuch, 2014).

The relationship between an observed variable and a component/factor is expressed by a *factor loading* (ranging from 0 – 1), which measures the amount of the variance in the variable explained by the component/factor. A factor loading of > 0.4 generally indicates that the variable can be attributed to the factor (Cutillo, 2019). A factor loading matrix shows the relationship between the factors and the original variables, with components/factors typically named by the common attributes of the set of variables with which they are most correlated. Neither EFA nor PCA provide a unique solution, as component/factor rotation allows for an infinite number of possible representations. The rotation can be chosen to maximise simplicity, interpretation or replicability (Fabrigar, Wegener, MacCallum, & Strahan, 1999). Two common types of rotation are orthogonal rotation (e.g. Varimax and Quartimax rotation); where the components/factors remain uncorrelated with each other, and oblique rotation (e.g. Promax rotation); which allows for correlation.

In the Figure 1 we provide a graphical representation of the relationship between observable and latent variables when working with two apparently similar concepts of *hospitalization stress* and *hospitalization related stressors* in two studies with two different objectives.

Research assessing *hospitalization stress* may use a large number of potential variables (e.g. loneliness, aggression, sense of loss, fear of death). Factor analysis may identify two underlying factors, *security* and *attachment* to which the variables load, with two variables loading to each factor. If one variable is hypothesized to be more related to one factor than another, this quantitative distinction can also be checked by EFA (Gorsuch, 2014). Alternatively, for a study on *hospitalization related stressors* there may be a large set of situations in hospital settings that may be associated with perceiving stress during the hospital stay. For a study measuring four variables: a) mobility limitation due to connected equipment; b) limited contact with family and relatives; c) stigma of being in hospital; and d) sleepless due to noisy rooms, PCA may have identified two principal components *physical agents* and *psychosocial agents* representing the four variables. The left side of Figure 1 shows PCA as a data reduction process identifying two principal components; while the right side shows EFA as a structure identification process comprising two latent factors.

INSERT FIGURE 1 HERE

3. Differences between EFA and PCA

EFA and PCA are related but conceptually distinct techniques (Basto & Pereira, 2012). PCA reduces the number of variables extracting the essence of the dataset by creating principal components, while EFA uncovers the constructs underlying the data and identifies latent factors to explain the data. In the examples shown in Figure 1, EFA identified two underlying factors that account for variability of variables assessing patient stress, while PCA reduced the measured hospitalization stressors into two principal components.

The focus of EFA is the relationship among the variables, while PCA has more emphasis on data reduction than interpretation. PCA aims to explain the maximum amount of the total variance in the variables by analyzing all of the observed variance, while in EFA, only the shared covariance between the variables is analyzed (Schneeweiss & Mathes, 1995). PCA is undertaken when there is sufficient correlation among the original variables. EFA is appropriate when we expect that there is a latent trait or unobservable characteristics among the observed variables. EFA and PCA also have different model assumptions regarding the data structure.

There are reasons that encourage researchers to use PCA rather than EFA. There are circumstances (e.g. where the error variances are small or similar) in which PCA could be considered as a good approximation of EFA leading to yield similar output statistics (Rao & Sinharay, 2007). Another reason for increased use of PCA is that it is usually the default option in some statistical software packages increasing its use despite other approaches (Basto & Pereira, 2012; Hooper, 2012). An awareness of the differences between PCA and EFA allows for alignment between statistical approach and research objectives, and ensures appropriate interpretation of results (Santos et al., 2019).

Both EFA and PCA procedures identify patterns regardless of clinical knowledge behind those variables. These procedures can be used when the researcher has limited information with regards to the latent structure (Lever, Krzywinski, & Altman, 2017; Pett, Lackey, & Sullivan, 2003) which may lead to less attention to the theoretical knowledge needed to select the appropriate procedure. Returning to Figure 1, hospitalization stress and hospitalization related stressors may seem similar, but the objectives of the study and nature of the observable variables determine which technique is appropriate. Where relevant clinical knowledge exists, this should be used as a guiding approach to any analysis, regardless of any existing or likely latent structure. Researchers should use theoretical knowledge for the selection of methods and techniques in EFA and PCA, but avoid retaining a theoretical basis unsupported by the analysis.

4. Interpreting factors and principal components

The results of EFA simply set out a number of factors, the meaning of which has to be deduced from the variables which load to the respective factors (Gorsuch, 2014). Instrument evaluation should distinguish between structures that are *reflective* (when variables are affected or explained by *effect indicators*) and *formative* (when variables are formed but not affected by *cause indicators*). The first structure constructs the *scale* and the second constructs the *index*, known as reflective and formative measures, respectively. It is important to know that PCA identifies a formative structure and is conceptually inappropriate for effect indicators and identifies a formative structure. Evaluation studies may inappropriately assume a reflective structure, and hence use EFA, where a formative structure is required. It is worth noting that the use of PCA does not imply the existence of a formative structure nor does using EFA imply an existing reflective structure, as both models could erroneously be used to analyze the same data and even yield similar results (Rao & Sinharay, 2007).

The researchers also need background knowledge to decide whether they are working with reflective or formative structures. In Figure 1, patient characteristic indicators of hospitalization stress have been treated as reflective indicators and have been subjected to

EFA, while hospital setting characteristics are treated as formative indicators of stress perceived during hospital stay (we called *hospitalization related stressors* to highlight their formative nature and distinguish with *hospitalization stress*) and have been subjected to PCA. All interpretations of factors/components based on loadings should be validated against external criteria (Gorsuch, 2014). If data reduction is the goal of analysis and the researcher is willing to have fewer dimensions through calculating weighted sums of indicators, PCA is the appropriate method and in this case, observed variables could not be considered as manifestations of components (Widaman, 1993).

In exploratory studies, the primary aim of the analysis is to examine the dataset to obtain the "best estimate" of the components or latent factors to model the structure (Bro & Smilde, 2014). It should be noted that factors in EFA should be interpreted as explanatory rather than causal. For PCA, the principal components may be challenging to interpret, especially in high-dimensional databases (Allen & Maletic-Savatic, 2011; Chao, Wu, Wu, & Chen, 2018).

5. Conclusion

While similar, EFA and PCA have different applications and interpretation. EFA is used to understand the underlying factors that are responsible for a set of observed variables, while PCA is used when the aim is data reduction. Given the problematic nature of causal language, a careful consideration of statistical procedure choice and research evidence reporting is important to minimize misinterpretation to better support the veracity of knowledge development (Thapa, Visentin, Hunt, Watson, & Cleary, 2020). As EFA and PCA have conceptual and statistical differences, attention to their characteristics is required to support accurate use and reporting so keep this in mind when you are deciding which one to use for your data needs.

References

Allen, G. I., & Maletic-Savatic, M. (2011). Sparse non-negative generalized PCA with applications to metabolomics. *Bioinformatics, 27*(21), 3029-3035. doi: 10.1093/bioinformatics/btr522

Basto, M., & Pereira, J. M. (2012). An SPSS R-menu for ordinal factor analysis. *Journal of Statistical Software, 46*(4), 1-29. doi: 10.18637/jss.v046.i04

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G.J. & Esquivel, S.L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research, and Evaluation, 18*(1), Article 6. doi: 10.7275/qv2q-rk76

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: a primer. *Frontiers in Public Health, 6*, Article 149. doi: 10.3389/fpubh.2018.00149

Bro, R., & Smilde, A. K. (2014). Principal component analysis. *Analytical Methods, 6*(9), 2812-2831. doi: 10.1039/C3AY41907J

Chao, Y. S., Wu, H. C., Wu, C. J., & Chen, W. C. (2018). Principal component approximation and interpretation in health survey and biobank data. *Frontiers in Digital Humanities, 5*, Article 11. doi: 10.3389/fdigh.2018.00011

Cutillo, L. (2019). Parametric and Multivariate Methods. In S. Ranganathan., M. Gribskov., K. Nakai., & C. Schönbach (Eds.), *Encyclopedia of bioinformatics and computational biology* (pp. 738-746). Amsterdam; Oxford; Cambridge: Elsevier.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272-299. doi: 10.1037/1082-989X.4.3.272

Gaskin, C. J., & Happell, B. (2014). On exploratory factor analysis: a review of recent evidence, an assessment of current practice, and recommendations for future use. *International Journal of Nursing Studies, 51*(3), 511-521. doi: 10.1016/j.ijnurstu.2013.10.005

Gorsuch, R. L. (2014). *Factor analysis: classic edition*. New York: Routledge Taylor & Francis.

Hooper, D. (2012). Exploratory factor analysis. In H. Chen (Ed.), *Approaches to quantitative research – theory and its practical application: A guide to dissertation students*. Cork, Ireland: Oak Tree Press.

Kline, P. (1994). *An easy guide to factor analysis*. London: Routledge. doi:10.4324/9781315788135

Lever, J., Krzywinski, M., & Altman, N. (2017). Principal component analysis. *Nature Methods, 14*, 641–642. doi: 10.1038/nmeth.4346

Meyers, L. S., Gamst, G., & Guarino, A. J. (2013). *Applied multivariate research: Design and interpretation*. Second edition. Thousand Oaks, California: SAGE Publications.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis.*. Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781412984898

Rao, C.R., Sinharay, S. (Eds.) (2007). *Handbook of statistics, volume 26: Psychometrics*. Amsterdam: Elsevier.

Santos, R. O., Gorgulho, B. M., Castro, M. A., Fisberg, R. M., Marchioni, D. M., & Baltar, V. T. (2019). Principal component analysis and factor analysis: Differences and similarities in nutritional epidemiology application. *Revista Brasileira de Epidemiologia, 22*, E190041. doi: 10.1590/1980-549720190041

Schneeweiss, H., & Mathes, H. (1995). Factor analysis and principal components. *Journal of Multivariate Analysis, 55*(1), 105-124. doi: https://doi.org/10.1006/jmva.1995.1069

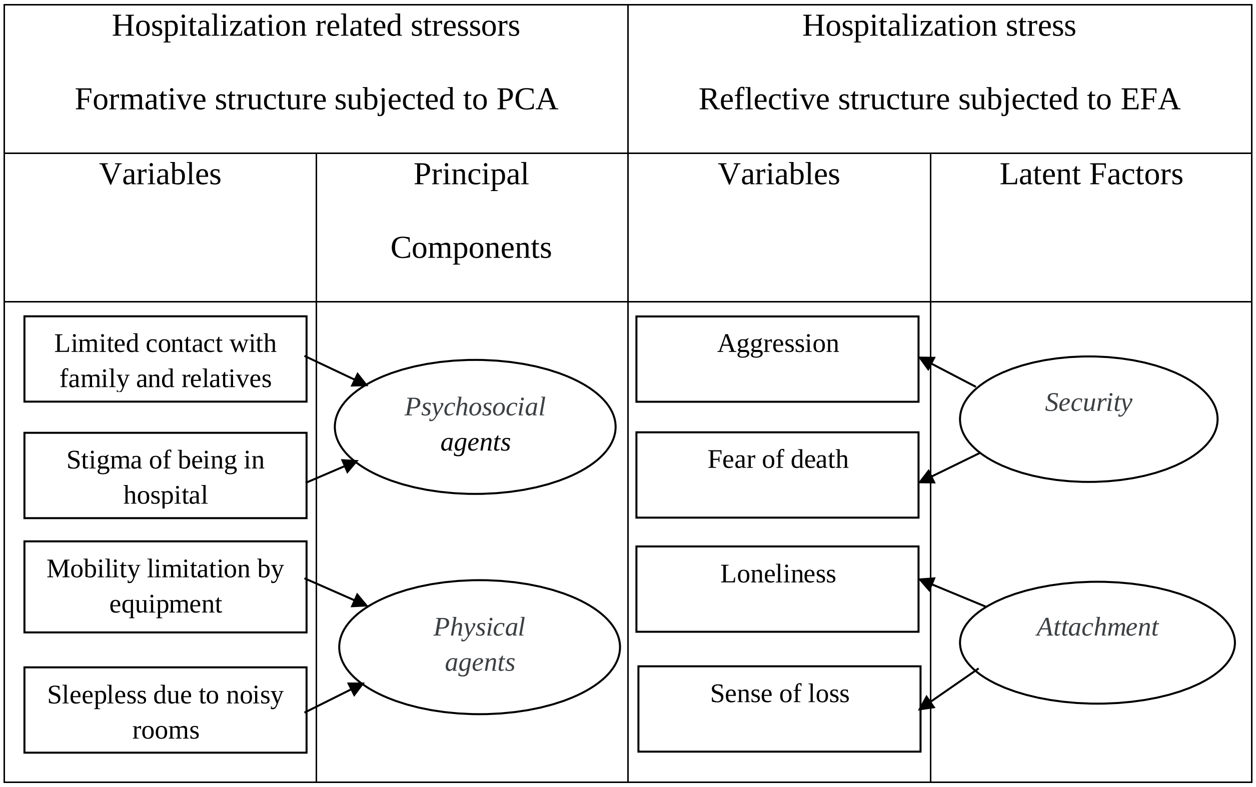
Tabachnick, B.G, & Fidell, L.S. (2001). *Using multivariate statistics*. Fourth Edition. Needham Heights, MA: Allyn & Bacon.

Thapa, D. K., Visentin, D. C., Hunt, G. E., Watson, R., & Cleary, M. (2020). Being honest with causal language in writing for publication. *Journal of Advanced Nursing*, doi: 10.1111/jan.14311

Watson, R., & Thompson, D. R. (2006). Use of factor analysis in Journal of Advanced Nursing: literature review. *Journal of Advanced Nursing. 55*(3), 330-341. doi: 10.1111/j.1365-2648.2006.03915.x

Widaman, K. F. (1993). Common factor analysis versus principal component analysis: Differential bias in representing model parameters? *Multivariate Behavioral Research, 28*(3), 263-311. doi: 10.1207/s15327906mbr2803_1

Figure 1: Illustrative example showing direction of association between components/factors and respective indicators in PCA and EFA approaches


Hospitalization related stressors
Formative structure subjected to PCA
Hospitalization stress
Reflective structure subjected to EFA
Variables
Principal Components
Variables
Latent Factors
Limited contact with family and relatives
Stigma of being in hospital
Mobility limitation by equipment
Sleepless due to noisy rooms
Psychosocial agents
Physical agents
Aggression
Fear of death
Loneliness
Sense of loss
Security
Attachment