Tehran University of Medical Sciences

Nursing Practice Today

2026; Volume 13, No 3, pp. 242-245

Commentary

Three common pitfalls in psychometric validation: PCA misuse, orthogonal rotation, and skipping confirmatory factor analysis

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Introduction

Validation of measurement instruments is a fundamental step in nursing and health sciences research, as the quality of research findings largely depends on the accuracy and validity of the instruments employed. In recent years, statistical methods have been widely applied to examine the construct validity of questionnaires in empirical studies. However, methodological literature suggests that in some cases, the selection or application of factor analytic techniques has been accompanied by challenges that may influence the interpretation of the underlying structure of measurement instruments. Given the importance of this issue, the present commentary aims to highlight several methodological considerations regarding instrument validation in nursing and health sciences research.

Specifically, three issues are discussed: the use of principal component analysis instead of exploratory factor analysis, the application of Varimax orthogonal rotation in situations where constructs are likely to be correlated, and limiting analyses to the exploratory stage without conducting confirmatory factor analysis to test the proposed structure. Addressing these methodological considerations may help clarify important aspects of validation studies and contribute to improving the rigor and accuracy of psychometric analyses in future research.

Use of Principal Component Analysis (PCA) Instead of Exploratory Factor Analysis (EFA)

One relatively common methodological issue in psychometric research is the use of principal component analysis (PCA) instead of exploratory factor analysis (EFA) when examining the construct structure of measurement instruments. In many studies in the behavioral sciences and health research, the primary aim of data analysis is to identify latent constructs that explain the pattern of correlations among observed questionnaire items. Methodologically, this objective is more consistent with the framework of exploratory factor analysis, as EFA is specifically designed to identify underlying latent factors. Nevertheless, in some studies, PCA is used in place of common factor extraction methods, even though this technique was originally developed for a different purpose (1).

One reason for this confusion relates to how these procedures are presented in statistical software. In programs such as SPSS, factor analysis and principal component analysis are located within the same analytical menu, and PCA is often displayed as the default extraction method. This presentation may create the impression that PCA and factor analysis are essentially equivalent techniques. In reality, however, they differ substantially in both their objectives and statistical foundations (2).

Conceptually, PCA is a data reduction technique designed to summarize information contained in a set of observed variables. In this method, the original variables are transformed into a smaller number of components, which are linear combinations of the initial variables. The goal is to produce components that explain as much of the total variance in the data as possible (3). Importantly, PCA includes all sources of variance in the analysis, including shared variance among variables, unique variance specific to each variable, and measurement error variance. As a result, the method does not

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DOI: 10.18502/npt.v13i3.22126

Please cite this article as: Ghanei Gheshlagh R. Three common pitfalls in psychometric validation: PCA misuse, orthogonal rotation, and skipping confirmatory factor analysis. Nursing Practice Today. 2026; 13(3):242-245.

distinguish between different sources of variance and focuses solely on maximizing the variance explained by the components (4). For this reason, the components extracted through PCA do not necessarily represent meaningful psychological constructs, but rather statistical combinations of observed variables.

In contrast, exploratory factor analysis (EFA) is grounded in the concept of latent variables. This approach assumes that the correlations among questionnaire items arise from a smaller number of underlying factors that are not directly observable but can be inferred from the pattern of responses (5). Within the factor analytic model, the variance of each observed variable is partitioned into three components: common variance, unique variance, and error variance.

Common variance represents the portion of variability shared among several items and explained by the underlying latent factors. In factor analysis, this quantity is expressed through the concept of communality, usually denoted as h^2, which indicates the proportion of variance in each variable accounted for by the common factors (2). Unique variance reflects the variance specific to an individual item, whereas error variance arises from measurement error or other random influences. In EFA, factor extraction is based solely on common variance. In other words, the primary goal of this method is to identify the latent structure responsible for the correlations among the observed items. This characteristic makes exploratory factor analysis a more appropriate method for examining the construct structure of questionnaires (1, 5).

The distinction between these two approaches can also influence analytical results. Because PCA incorporates all sources of variance in the data, it often produces a higher proportion of explained variance and larger factor loadings. Consequently, it may make the factor structure appear stronger than it actually is, potentially leading to interpretations that are theoretically or psychologically misleading (4). By contrast, common factor extraction methods such as Maximum Likelihood and Principal Axis Factoring, which focus on shared variance, tend to provide a more realistic representation of the underlying latent structure.

Methodological reviews have shown that the misuse of PCA in psychometric research is relatively common. For example, Fabrigar and colleagues (1999) reported that many psychological studies used PCA to extract factors even though the primary goal of those studies was to identify latent constructs (1). Similarly, Costello and Osborne (2005), in their review of studies in the behavioral sciences, found that a substantial proportion of published research relied on PCA rather than appropriate factor analytic methods (2). Conway and Huffcutt (2003), in their examination of studies in organizational psychology, also noted the widespread use of PCA in situations where common factor analysis would have been more appropriate (6).

One historical reason for the widespread use of PCA is its computational simplicity. Before the widespread availability of computers and statistical software, performing factor analysis was relatively complex and time-consuming, whereas PCA was easier to compute. However, with the development of modern statistical software, this limitation has largely disappeared, and researchers can now readily apply appropriate common factor extraction methods (1).

Overall, distinguishing between PCA and exploratory factor analysis is critically important in psychometric research. When the goal of a study is to identify or validate the latent constructs underlying a measurement instrument, exploratory factor analysis with appropriate extraction methods, such as Maximum Likelihood or Principal Axis Factoring, is generally recommended. Using an inappropriate analytical method may influence both the statistical results and the theoretical interpretation of the instrument's structure. Therefore, careful attention to the methodological foundations of factor analysis can play an important role in improving the accuracy and validity of psychometric studies.

Inappropriate rotation

The second issue concerns the use of Varimax rotation in the study. In factor analysis, rotation is applied to improve the interpretability of extracted factors, as the initial factor solution is often ambiguous and difficult to interpret. The aim of rotation is to achieve a simple structure, in which each variable loads strongly on one factor while having minimal loadings on the others, thereby producing a clearer and more interpretable pattern of factor loadings (7).

Varimax is an orthogonal rotation method in which the angle between factors is constrained to 90 degrees. Consequently, this approach assumes that the extracted factors are completely uncorrelated (1). Because it often produces a clean and easily interpretable structure, Varimax has been widely used in many studies (8).

However, its application in behavioral and health sciences warrants careful consideration. Psychological and behavioral constructs are typically related to one another, and the assumption of complete independence among factors is often unrealistic. Imposing an orthogonal rotation under such circumstances may therefore lead to an artificial and less realistic factor structure.

In contrast, oblique rotation methods allow factors to be correlated. If the factors are truly independent, oblique rotations will also yield correlations close to zero. However, when relationships among constructs exist, as is often the case in behavioral research, these methods provide a more realistic and theoretically meaningful representation of the data (8). For this reason, many psychometric methodologists recommend the use of oblique rotations, such as Promax or Direct Oblimin, when analyzing constructs in the behavioral and social sciences in order to better capture the underlying latent structure (2, 9).

Lack of Confirmatory Factor Analysis

The third significant issue is the reliance solely on exploratory methods, without employing Confirmatory Factor Analysis (CFA) to assess construct validity. When a theoretical model exists and the sample size is sufficient, omitting CFA can be considered a methodological limitation.

Exploratory factor analysis (EFA) is primarily used to identify or propose potential latent structures within the data, but it is not designed to rigorously test these structures. In contrast, CFA is specifically developed to test a priori hypotheses about the factor structure of a measurement instrument and to evaluate the degree to which empirical data fit a theoretically specified model (10). In CFA, researchers define the expected factor structure in advance and then assess the fit of this model to the observed data using various model fit indices.

This approach also allows researchers to examine the extent to which each item loads on its intended factor and to compare alternative structural models (11). By contrast, results obtained from EFA are inherently exploratory, and the resulting factor solution may depend partly on researchers' analytical decisions.

These analytical decisions are not merely technical; they hold significant practical consequences for the interpretation of the instrument. A prime example is the choice of factor rotation. While orthogonal rotation forces factors to be independent, oblique rotation permits correlations among them. Given that psychological constructs are typically interrelated, the use of orthogonal methods is rarely defensible; consequently, researchers should prioritize oblique rotation to provide a more realistic representation of the underlying data.

These choices are far from trivial, as they directly influence factor loadings, dimensionality, and the resulting conceptual framework. Since such decisions fundamentally shape the final structure of the scale, they underscore the necessity of moving beyond EFA to conduct a CFA, which allows for a more rigorous and theoretically grounded evaluation of the instrument's construct validity (12). Consequently, different researchers analyzing the same dataset may arrive at different factor solutions (13). For this reason, contemporary psychometric literature emphasizes that structures identified through EFA should subsequently be tested using CFA in order to provide a more rigorous evaluation of the instrument's structural validity (11, 13).

Moreover, many methodological guidelines recommend that exploratory and confirmatory analyses be conducted on two independent samples (cross-validation) whenever possible, in order to reduce the risk of overfitting the model to the original dataset. Therefore, restricting the analysis to the exploratory stage without conducting CFA may limit a comprehensive assessment of the instrument's construct validity (5).

It is hoped that these methodological considerations can contribute to a constructive scientific discussion and help improve the standards of instrument validation in nursing and health sciences research, guiding future researchers toward more appropriate analytical approaches.

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