Exploratory Factor Analysis in *Rehabilitation Psychology*: A Content Analysis

Richard B. Roberson III, Timothy R. Elliott, Jessica E. Chang, and Jessica N. Hill
Texas A&M University

**Objective:** Our objective was to examine the use and quality of exploratory factor analysis (EFA) in articles published in *Rehabilitation Psychology*. **Design:** Trained raters examined 66 separate exploratory factor analyses in 47 articles published between 1999 and April 2014. The raters recorded the aim of the EFAs, the distributional statistics, sample size, factor retention method(s), extraction and rotation method(s), and whether the pattern coefficients, structure coefficients, and the matrix of association were reported. **Results:** The primary use of the EFAs was scale development, but the most widely used extraction and rotation method was principle component analysis, with varimax rotation. When determining how many factors to retain, multiple methods (e.g., scree plot, parallel analysis) were used most often. Many articles did not report enough information to allow for the duplication of their results. **Conclusion:** EFA relies on authors’ choices (e.g., factor retention rules extraction, rotation methods), and few articles adhered to all of the best practices. The current findings are compared to other empirical investigations into the use of EFA in published research. Recommendations for improving EFA reporting practices in rehabilitation psychology research are provided.

**Keywords:** exploratory factor analysis, rehabilitation, guidelines, research methods, statistical analysis

**Impact and Implications**

- This paper provides the first analysis and critique of the use of exploratory factor analysis in papers published in *Rehabilitation Psychology*.
- This paper provides guidelines for conducting and reporting an exploratory factor analysis and it provides an explanation of concepts associated with exploratory factor analysis.
- This paper recommends that multiple techniques (e.g., orthogonal and oblique rotation; scree plot, parallel analysis) be used when conducting an exploratory factor analysis. Using multiple techniques will provide the most accurate and stable set of factors.

**Introduction**

In psychological research, the main purpose of exploratory factor analysis (EFA) is to identify the underlying latent variables or factors of a measure by exploring the relationship among observed variables (Gorsuch, 1983). EFA allows more subjectivity in the decision-making process than many other statistical procedures (Thompson, 2004). However, critics find fault with this subjectivity (Ehrenberg & Goodhardt, 1976; Floyd & Widaman, 1995). Consequently, there are guidelines to inform decisions about how to conduct an EFA and to promote best practices with EFA.

Although guidelines for best practices on conducting an EFA (Comrey, 1978; Ford, MacCallum, & Tait, 1986; Jackson, Gillespy, & Purc-Stephenson, 2009) and for making informed decisions on ways to improve the interpretation of EFA exist (Henson & Roberts, 2006; Steger, 2006), there is evidence that these guidelines are often not employed in research utilizing EFAs. For example, Fabrigar, Wegener, MacCallum, and Strahan (1999) found in two prominent applied psychology journals that articles featuring EFAs underreported critical information about the procedures that would aid interpretation. About 25% and 17% of the articles they reviewed did not report the extraction or rotation method, respectively, and nearly 40% of the articles they reviewed did not mention how they determined the number of factors to retain. Additionally, half of the studies used principle component analysis (PCA) with varimax rotation as the extraction and rotation method (Fabrigar et al., 1999). When the aim of the study is scale development, PCA is not as sound a method as using a common factor analysis extraction method (e.g., maximum likelihood, principal axis factoring [PAF]). PCA is, however, an appropriate extraction method if the aim is data reduction. In a review of 66 articles published in a developmental disability journal, Norris and Lecavalier (2010) found that the majority of studies did not follow guidelines of best practices when conducting an EFA. The matrix of association and pattern coefficients were rarely reported, and authors did not indicate or inform the readers where they could go to retrieve the information. This lack of detail compels readers to assume the researchers competently conducted an EFA.

Because EFA is an exploratory technique, it should be used for exploratory purposes, guidance in initial theory development but...
not for rigorous theory testing, confirmatory factor analysis is the appropriate technique for substantive theory testing (Hurley et al., 1997). Observing best practices in EFA reporting helps researchers with design and analytical choices that have a substantial impact on the results of an EFA. Recommended steps to take when conducting an EFA are contained in Table 1, and brief explanations of basic concepts associated with EFA are provided in Appendix A. These best practices provide a systematic way to approach an EFA to allay criticisms associated with this method, improve the generalizability and the stability of results, and help

<table>
<thead>
<tr>
<th>Procedural choices</th>
<th>Best practices</th>
<th>Reference</th>
</tr>
</thead>
</table>
| Distributional statistic(s) | 1. Use a Likert-type scale with a minimum of 3–4 items per theorized factor because it allows for greater variation in responses.  
2. Check to make sure variables are normally distributed. Specifically, skewness and kurtosis should be reported with results of the EFA. | Floyd and Widaman (1995); Smith and McCarthy (1995)                         |
| Sample and sample size      | 1. The sample should be representative of the population of interest.  
2. There is no set minimum number of participants for an EFA.  
Therefore, researchers should use multiple methods to determine an adequate sample size, for example, examining the ratio of participants to the number of variables, the pattern coefficients and/or the communalities. In general, an adequate sample is obtained when the average of the squared pattern coefficients are around 35% or higher, the average of the communalities is around 60%, and there are 100 participants or a 5:1 ratio of participants to questions, whichever is greater. If the squared pattern coefficients or communalities do not reach these levels, then more participants should be added until they approach these levels. | MacCallum, Widaman, Zhang, and Hong (1999); Norris and Lecavalier (2010); Reise, Waller, and Comrey, (2000) |
| Extraction                  | 1. There is no set extraction method. The extraction method should be dictated by the aim of the analysis. If the aim is data reduction, principal component analysis is appropriate. If the aim is scale development, a common factor analysis technique (e.g., maximum likelihood) is appropriate. When the aim is scale development, multiple extraction methods should be used to determine which method does the best job of producing interpretable latent variables or factors. | Daniel (1990); Thompson (2004)                                           |
| Rotation                    | 1. Both orthogonal (e.g., varimax, quartimax, equamax) and oblique (e.g., promax, oblimin, direct oblimin) rotation methods should be used to determine which method provides the best interpretation of the data when conducting an EFA.  
2. The law of parsimony should guide selection of rotation method: if "... two explanations fit a set of facts roughly equally, with all things being equal, the simpler explanation is most likely to be true" (Thompson, 2004, p. 70). In terms of rotation methods, orthogonal rotation is simpler and the results are more generalizable than oblique rotation. If the difference between orthogonal and oblique rotation are not substantial then an orthogonal rotation method is the more appropriate method, but this will only be known if orthogonal and oblique rotations are utilized. However, oblique rotation is recommended if the correlation between latent variables exceeds 10% (e.g., $r = .32$). | Sass and Schmitt (2010); Schmitt and Sass (2011) |
| Factor retention criteria   | 1. Before conducting an EFA, researchers should set a minimum level the pattern coefficients must reach to be included in a factor and the minimum number of pattern coefficients needed to form a factor.  
2. Researchers should select and employ multiple factor retention methods (e.g., the Guttman-Kaiser criterion, the scree test, parallel analysis, statistical tests, clinical significance, minimum average partial method) to determine the most parsimonious set of factors. | Hayton, Allen, and Scarpello (2004)                                       |
| Matrices to include         | 1. At a minimum, the matrix of association (e.g., correlation matrix, covariance matrix) with mean and standard deviation, and the full pattern coefficient matrix should be reported or made available in appendices.  
2. If an oblique rotation method is used, the inter-factor correlation matrix and the factor structure coefficients matrix should be made available in appendices. | Comrey (1978)                                                             |
| Justification for method selection | 1. Researchers should report the choices they make at each step and justify their choice of method.  
2. Enough information should be provided so that another researcher can replicate the results. | Comrey (1978)                                                             |

Note. EFA = exploratory factor analysis.
researchers select the correct methods to analyze their data. When poor designs or analytical choices are made, distortions can occur that obscure the underlying factor structure, produce uninterpretable factors and flawed conclusions. For example, when the aim of an EFA is identifying latent factors, the combination of PCA with varimax rotation can impede a researcher’s ability to produce stable and replicable factor analytic results (Comrey, 1978).

The use of factor analysis has been investigated in American Psychological Association journals (Jackson et al., 2009), industrial-organizational psychology outlets (Ford et al., 1986), the Journal of Personality and Social Psychology and the Journal of Applied Psychology (Fabrigar et al., 1999), measurement and educational journals (Henson & Roberts, 2006), and in several developmental disabilities outlets (Norris & Recalvair, 2010). Across these studies, PCA with varimax rotation was the most popular extraction and rotation method. In addition, researchers rarely followed all the guidelines when conducting an EFA and crucial information about the methods for deciding how many factors to retain or the type of matrix used was often omitted. However, a positive trend emerged in which the authors of later reviews reported that a greater number of articles were following more of the best practices.

Despite their frequent use in rehabilitation research, the common methods for EFA have not been examined in papers appearing in Rehabilitation Psychology (RP). We do not know if articles in RP follow best practice guidelines in conducting and reporting EFAs. This paper provides the first systematic examination of EFAs appearing in RP to determine how closely authors follow best practice guidelines and to identify areas of improvement. We examined the way EFA techniques were reported in RP over the past 15 years (1999 to April 2014). Specifically, we examined reporting practices in six areas: (a) the distributional statistic(s) reported, (b) sample size, (c) the extraction method(s), (d) the rotation method(s), (e) factor retention method(s), and (f) matrices to include (e.g., pattern coefficients, structure coefficients or matrix of association). In addition, we determined if EFA was used for data reduction or scale development and discuss guidelines and issues that should be considered in conducting and reporting EFAs.

**Method**

**Procedures**

Articles published in RP from 1999 to April 2014 were reviewed for use of an EFA. Keywords (i.e., “factor analysis,” “rotation,” “principal component,” “extraction,” “eigenvalue,” “oblique,” “orthogonal,” and “scree”) were used to determine the articles that used EFA. The search yielded 47 articles. After collecting the articles, two trained raters analyzed the published papers to determine what information the authors reported. Specifically, the raters recorded whether the authors provided information on the distributional statistic(s), ratio of participants to number of variables, sample size, extraction method(s), method(s) for determining the number of factors to retain, rotation method(s), and whether tables with critical information (e.g., matrix of association, pattern coefficient matrix, intrafactor matrix) were provided. Additionally, the aim of the EFAs (i.e., scale development or data reduction) was recorded. An Excel spreadsheet was used to record this information to allow raters to determine which methods were used most often. The 47 articles contained 66 separate analyses; 10 articles reported multiple EFAs. We used the total number of analyses to calculate the percentage of EFAs that reported the information, except when subgroups were analyzed; then, the total for the subgroup was used.

**Data Analysis**

To ensure a high level of agreement between the raters, the percent agreement was calculated. The aim was to achieve an initial average agreement rate of 80% between raters. Simple descriptive statistics were used to determine the percentage of EFAs that reported the information under investigation. The percentage of EFAs reporting a specific variable was determined by dividing how often the specific variable was reported by the total number of EFAs (n = 66) or the total of a subgroup. For example, if the 20 EFAs used an orthogonal rotation method and 10 used varimax rotation, the percentage of EFAs reporting this information would be 20/66 (30.3%) and 10/20 (50%). This method was repeated for all of the categories under investigation. If more than one extraction, rotation, or factor retention method was used, it was recorded as using multiple methods.

**Raters**

Two doctoral graduate students were trained to analyze the selected articles to determine what information was reported. The raters were unfamiliar with EFA as a statistical technique before training. The training consisted of reading two articles (Costello & Osborne, 2005; Fabrigar et al., 1999) that report the rationale and methods used in the present study. In addition, they read four book chapters from Thompson (2004) to obtain a basic conceptual understanding of EFA. The lead author met individually with the raters to teach them how to search an article for the appropriate information. To practice, the raters searched through five articles each and recorded their information in an Excel spreadsheet. After each article, the rater and the lead investigator discussed whether all the pertinent information was obtained and whether any superfluous information was collected. To resolve discrepancies, raters were asked to reread the article(s) in question. If disagreement persisted, the two raters discussed it with the lead investigator and reached a consensus.

**Variables Rated for Each EFA**

For every paper in which an EFA appeared, raters coded and rated several features for which best practices currently exist (see Table 1): (a) distributional statistic(s), (b) sample size, (c) the extraction method(s), (d) the rotation method(s), (e) factor retention criteria, and (f) matrices to include. Additionally, the aim of the study was recorded as data reduction or scale development.

**Distributional statistic(s).** It is recommended that the questionnaire used in an EFA have at least three questions per proposed factor (Thompson, 2004) that are normally distributed (Smith & McCarthy, 1995). Raters were instructed to record information on skewness and kurtosis (common measures of distribution).

**Sample size.** It is recommended that samples be representative of the population of interest and that multiple methods be used to determine the sample size (Reise, Waller, & Comrey, 2000). For
example, the sample size should be calculated using the ratio of participants to the number of questions, the value of the squared pattern coefficient and the communalities (MacCallum, Widaman, Preacher, & Hong, 2001). This is important because if an inadequate sample size is used, the results from the EFA will not be stable or replicable. The raters recorded the exact sample size and the number of items in the questionnaire. With this information, raters were able to record the ratio of participants to number of items.

**Extraction.** It is recommended that multiple extraction methods be used when conducting an EFA (Daniel, 1990; Thompson, 2004). When the aim is data reduction PCA is appropriate, but when the aim is scale development, reliance on PCA can produce unreliable results. A common factor analysis extraction method (e.g., PAF, maximum likelihood) should be used when the aim is scale development. Raters recorded the extraction method reported, and if no information was provided, it was recorded as unknown.

**Rotation.** It is recommended that multiple rotation methods be used when implementing an EFA (Sass & Schmitt, 2010; Schmitt & Sass, 2011). It is unwarranted to assume a priori that psychological constructs are truly independent. If an author suspects that factors are uncorrelated an oblique rotation should be performed to ascertain the level of overlap and if there is no overlap, the analysis can be rerun with an orthogonal rotation. This is important because orthogonal rotation is more generalizable and mathematically simple, while oblique rotation often better represents the data and is more mathematically complex. This guideline requires the author(s) to choose the method that will provide the most parsimonious explanation. Raters recorded if the rotation method was orthogonal or oblique and recorded the specific rotation method for the orthogonal or oblique rotations. If no method was mentioned, it was recorded as unknown.

**Factor retention criteria.** It is recommended that before conducting an EFA, researchers need to determine the criteria they will use to retain factors (Hayton, Allen, & Scarpello, 2004). Multiple criteria should be used, such as the “eigenvalue-greater-than-one” rule (the Guttman–Kaiser criterion; Yeomans & Golder, 1982), the scree test, parallel analysis, and statistical tests in order to retain the optimal number of factors. Retaining too many or too few factors will negatively impact interpretation. Raters recorded the factor retention methods. If there was no information, it was listed as unknown.

**Matrices to include.** It is recommended that authors include the matrix of association, factor pattern and structure coefficient matrices, interfactor correlation matrix, or submit them as supplemental information (Comrey, 1978). This is important because the results can be replicated using the matrix of association and because these matrices aid in evaluating the results of an EFA. Raters recorded whether the matrix of association, pattern and structure coefficient matrices, and the correlation between factors was reported.

**Aim of the study.** The raters recorded whether the aim of the study was data reduction or scale development. This is important because the aim of the study should dictate the methods used to analyze the data.

## Results

### Rater Agreement

The initial average percent agreement between raters across all categories was 89.8%. The discrepancies occurred in rating two articles. These two articles reported multiple EFAs and one rater failed to record the information for the second and subsequent EFAs.

### Main Analysis

The results are summarized in Table 2. Forty-seven articles (out of n = 655 total papers) reported an EFA between 1999 and April 2014 (for references of articles included in the main analysis; see Appendix B in the online supplemental materials). Of the articles that featured an EFA, several (n = 10) reported multiple EFAs. The results are based on the 66 analyses extracted from the 47 articles.

Overall, 82% (n = 54) of the studies used EFA for scale development. Skewness and kurtosis were each reported in 4% (n = 3) of the studies. However, no single study reported both skewness and kurtosis.

Over 60% (n = 40) of the EFAs used samples with a ratio of participants to the number of measured variables greater than 6:1, but nearly 17% (n = 11) of analyses used ratios less than 2:1. Almost a quarter of the studies had samples sizes with ratios between 3:1 and 6:1. Sample sizes varied greatly: Over 72% (n = 48) of the analyses used samples between 100 and 300 participants, and 16.7% (n = 11) of the EFAs had samples of over 300 participants. However, 11% (n = 7) of the EFAs had samples with fewer than 100 participants.

Principal component analysis was the most commonly used extraction method, appearing in 59.1% (n = 39) of the 66 analyses. In the 39 analyses that used PCA, it was used to identify latent factors 82% (n = 32) of the time. Two analyses used maximum likelihood as the extraction method to identify latent factors. Thirty percent (n = 20) of the 66 analyses used PAF as the extraction method. In the 20 analyses that used PAF, it was used to identify latent factors 75% (n = 15) of the time. The use of multiple extraction methods was used in two analyses to identify latent factors. Two analyses did not report the extraction method used, but they were used to identify latent factors.

Orthogonal rotation was used in 45% (n = 30) of the 66 analysis. Varimax rotation was used in 93.3% (n = 28) of the 30 analyses that used an orthogonal rotation. In addition, one analysis used equimax and one analysis mentioned using an orthogonal rotation method, but failed to report the specific method used. Within oblique rotation (n = 22), promax rotation was used 68.2% (n = 15) of the time. One analysis used an oblimin rotation, and 27% (n = 6) out of the 22 analyses that used an oblique rotation did not indicate the specific oblique method used. Nearly 14% (n = 9) of the studies used multiple rotation methods, and about 8% (n = 5) did not report any information on the rotation method used.

A variety of methods was used to determine the number of factors to retain. The three most popular methods were multiple methods (43.9%, n = 29), the eigenvalue-greater-than-one rule (27.5%, n = 18), and unknown method(s) (12.2%, n = 8). When
multiple methods were used, it was usually the eigenvalue-greater-than-one rule and the scree test. Parallel analysis was used in almost 8% ($n/110055$) of the analyses. Only 10.6% ($n/110057$) included or offered to make available the matrix of association used. Almost 64% ($n/1100542$) of the analyses provided the factor pattern coefficient matrix. Of the 31 analyses that used an oblique rotation in isolation or in conjunction with orthogonal, 45.2% ($n/1100514$) included the correlations among the factors, but none of these studies included the factor structure coefficient matrix.

**Discussion**

This is the first study to detail the methods used and reporting habits of published EFAs in RP. Forty-seven articles containing 66 separate EFAs were evaluated in this review of the use of EFAs in RP between 1999 and April 2014. Of note, many researchers observed best practices by reporting the specific extraction and rotation methods employed, by reporting the factor pattern coefficient matrix, by using adequate sample sizes, and by using multiple methods to determine the number of factors to retain. Observing these best practices is important because reporting the extraction and rotation methods provides others with information they can use to replicate the results; reporting the factor pattern coefficient matrix allows readers to make their own interpretations about which pattern coefficients are associated with which factors; using adequate sample sizes allows for greater trust in the results and in their replicability; and using multiple methods allows researchers to identify the most interpretable, reliable and parsimonious factor structure (Thompson, 2004). A formal trend analysis was not conducted, but the results over the 15 years indicate that analyses published in the early 2000s used PCA the most, but in papers published after 2009, PAF was used more frequently.

In comparisons with other reviews, our findings reflect that some best practice recommendations are used as frequently and in some cases more frequently in RP research studies. For example, in the current study only 3%, 8%, and 12% of the studies, respectively, failed to report the extraction method, the rotation method

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**Table 2 (continued)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>EFAs performed</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Covariance matrix</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>0/66</td>
<td>0%</td>
</tr>
<tr>
<td>No</td>
<td>66/66</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Factor pattern coefficient matrix</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>42/66</td>
<td>63.64%</td>
</tr>
<tr>
<td>No</td>
<td>24/66</td>
<td>36.36%</td>
</tr>
<tr>
<td>*<em>Factor structure coefficient matrix (only for oblique rotations)</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>0/31</td>
<td>0%</td>
</tr>
<tr>
<td>No</td>
<td>31/31</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Interfactor correlations (only for oblique rotations)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>14/31</td>
<td>45.16%</td>
</tr>
<tr>
<td>No</td>
<td>17/31</td>
<td>54.84%</td>
</tr>
</tbody>
</table>

* One would make available upon request. * Includes analyses using multiple rotation methods where one was an oblique rotation.

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**Table 2**

*Summary of Use of Exploratory Factor Analysis in Rehabilitation Psychology Between 1999 and April 2014*

<table>
<thead>
<tr>
<th>Variable</th>
<th>EFAs performed</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aim of EFA</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used for scale development</td>
<td>54/66</td>
<td>81.82%</td>
</tr>
<tr>
<td>Data reduction</td>
<td>11/66</td>
<td>16.67%</td>
</tr>
<tr>
<td>Both</td>
<td>1/66</td>
<td>1.51%</td>
</tr>
<tr>
<td><strong>Ratio of participants to number of variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2:1$</td>
<td>11/66</td>
<td>16.67%</td>
</tr>
<tr>
<td>$3:1$ to $4:1$</td>
<td>9/66</td>
<td>13.64%</td>
</tr>
<tr>
<td>$5:1$ to $6:1$</td>
<td>6/66</td>
<td>9.09%</td>
</tr>
<tr>
<td>$&gt;6:1$</td>
<td>40/66</td>
<td>60.61%</td>
</tr>
<tr>
<td>Unknown</td>
<td>0/66</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Sample size</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$&lt;100$</td>
<td>7/66</td>
<td>10.61%</td>
</tr>
<tr>
<td>$101$–$200$</td>
<td>34/66</td>
<td>51.52%</td>
</tr>
<tr>
<td>$201$–$300$</td>
<td>14/66</td>
<td>21.21%</td>
</tr>
<tr>
<td>$&gt;300$</td>
<td>11/66</td>
<td>16.67%</td>
</tr>
<tr>
<td>Unknown</td>
<td>0/66</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Checks on distributional properties</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>3/66</td>
<td>4.54%</td>
</tr>
<tr>
<td>No</td>
<td>63/66</td>
<td>95.45%</td>
</tr>
<tr>
<td>Kurtosis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>3/66</td>
<td>4.54%</td>
</tr>
<tr>
<td>No</td>
<td>63/66</td>
<td>95.45%</td>
</tr>
<tr>
<td><strong>Extraction method</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal component analysis</td>
<td>39/66</td>
<td>59.09%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>32/39</td>
<td>82.05%</td>
</tr>
<tr>
<td>Used for data reduction</td>
<td>6/39</td>
<td>15.38%</td>
</tr>
<tr>
<td>Used for both</td>
<td>1/39</td>
<td>2.56%</td>
</tr>
<tr>
<td>Maximum likelihood</td>
<td>2/66</td>
<td>3.03%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>2/2</td>
<td>100%</td>
</tr>
<tr>
<td>Principal axis factors</td>
<td>20/66</td>
<td>30.30%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>15/20</td>
<td>75%</td>
</tr>
<tr>
<td>Used for data reduction</td>
<td>5/20</td>
<td>25%</td>
</tr>
<tr>
<td>Least square</td>
<td>1/66</td>
<td>1.51%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>1/1</td>
<td>100%</td>
</tr>
<tr>
<td>Multiple methods</td>
<td>2/66</td>
<td>3.03%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>2/2</td>
<td>100%</td>
</tr>
<tr>
<td>Unknown</td>
<td>2/6</td>
<td>3.03%</td>
</tr>
<tr>
<td>Used for scale development</td>
<td>2/2</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Factor retention methods</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eigenvalue $&gt;1$</td>
<td>18/66</td>
<td>27.28%</td>
</tr>
<tr>
<td>Scree test</td>
<td>6/66</td>
<td>9.09%</td>
</tr>
<tr>
<td>Parallel analysis</td>
<td>5/66</td>
<td>7.57%</td>
</tr>
<tr>
<td>Multiple methods</td>
<td>29/66</td>
<td>43.94%</td>
</tr>
<tr>
<td>Unknown methods</td>
<td>8/66</td>
<td>12.12%</td>
</tr>
<tr>
<td><strong>Rotation method</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orthogonal</td>
<td>30/66</td>
<td>45.45%</td>
</tr>
<tr>
<td>Varimax</td>
<td>28/30</td>
<td>93.33%</td>
</tr>
<tr>
<td>Equimax</td>
<td>1/30</td>
<td>3.33%</td>
</tr>
<tr>
<td>Unknown</td>
<td>1/30</td>
<td>3.33%</td>
</tr>
<tr>
<td>Oblique</td>
<td>22/66</td>
<td>33.33%</td>
</tr>
<tr>
<td>Promax</td>
<td>15/22</td>
<td>68.18%</td>
</tr>
<tr>
<td>Oblimin</td>
<td>1/22</td>
<td>4.54%</td>
</tr>
<tr>
<td>Unknown</td>
<td>6/22</td>
<td>27.27%</td>
</tr>
<tr>
<td>Multiple methods</td>
<td>9/66</td>
<td>13.64%</td>
</tr>
<tr>
<td>Unknown method</td>
<td>5/66</td>
<td>7.57%</td>
</tr>
<tr>
<td><strong>Tables</strong></td>
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<tr>
<td>Correlation matrix*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>7/66</td>
<td>10.61%</td>
</tr>
<tr>
<td>No</td>
<td>59/66</td>
<td>89.39%</td>
</tr>
</tbody>
</table>

* EFA = exploratory factor analysis. * Includes analyses using multiple rotation methods where one was an oblique rotation.
and the method(s) used to retain factors. In other journals, the extraction method, rotation method, and factor retention methods were omitted in 5%, 8%, and 8% of the studies (Norris & Lecavalier, 2010) and in 23%, 8%, and 30% of the studies (Ford et al., 1986). EFAs in RP used multiple methods for determining how many factors to retain with greater frequency than earlier EFA reviews. Multiple factor retention methods were used about 44% of the time in RP articles and, in other journals, 14% (Ford et al., 1986) and 20% (Fabrigar et al., 1999) of the time. Moreover, multiple rotation methods were used more frequently in the published RP studies when compared to earlier EFA reviews. Fabrigar et al. (1999) stated that about 3% of the articles used multiple rotation methods. In the current study, 14% used multiple rotation methods. However, only 3% of the analyses used multiple extraction methods. This frequency approximated the rate found by Fabrigar et al. (1999). These results indicate that researchers used multiple methods with greater frequency, but the majority of articles still relied on a single method (e.g., rotation, extraction) to analyze the data. Multiple methods should be used because they help to produce the best results (Henson & Roberts, 2006).

Although the use of PCA is the predominant extraction method, researchers in RP are using other types of extraction methods with greater frequency. In the review by Henson and Roberts (2006), 22% of the studies used PAF, and, in the current study, 30% of the analyses used PAF. The majority of samples in the current study had a ratio of participants to variables exceeding 5:1, which is comparable to what has been observed in other reviews (Fabrigar et al., 1999; Ford et al., 1986; Norris & Lecavalier, 2010). Orthogonal rotation was used less frequently and oblique rotation was used more frequently in RP studies when compared to other reviews. Earlier reviews found that 80% of studies used an orthogonal rotation, and 12% used an oblique rotation (Ford et al., 1986). The frequency of orthogonal and oblique rotation in RP is about 50% and 35%, respectively. Our results show researchers are utilizing some of the recommendations and best practices concerning EFAs.

In previous studies of EFA usage, PCA and varimax rotation was the most common extraction and rotation method (Fabrigar et al., 1999; Ford et al., 1986; Henson & Roberts, 2006; Norris & Lecavalier, 2010; Worthington & Whitaker, 2006). This is true for the current study, but it is problematic, because over 80% of the analyses stated goal was identification of latent factors. Thus, there was a mismatch between the methods used and the stated aim of the study. Published guidelines and articles reviewing EFA practices warn against relying on PCA with varimax rotation when the aim is not data reduction (Costello & Osborne, 2005; Fabrigar et al., 1999; Preacher & MacCallum, 2003; Worthington & Whitaker, 2006). Authors apparently persist in using it to analyze their data.

The drawback to using PCA when the aim is identifying latent variables is the tendency of PCA to overestimate the amount of variance contained in each factor because the variance associated with sampling and measurement error is not removed like it is in other extraction methods (e.g., maximum likelihood, PAF; Fabrigar et al., 1999). Another issue is that PCA with orthogonal rotation is more likely to produce factors that are not as replicable or as stable as other extraction and rotation combinations (Costello & Osborne, 2005). In their study, Costello and Osborne (2005) showed how PCA on average overestimated the variance the factors accounted for by 16% and inflated the pattern coefficients. Using data collected by Breckler (1984), Fabrigar et al. (1999) compared the results of two EFAs: one was conducted using PCA with varimax rotation (orthogonal rotation), and the other EFA used maximum likelihood with direct quartimin rotation (oblique rotation). The analysis using PCA with varimax rotation, again, inflated the pattern coefficients and substantially increased the number of cross-loading pattern coefficients when compared to the EFA using maximum likelihood with direct quartimin rotation.

Inflated and cross-loading pattern coefficients are problematic because they can distort how the factor pattern coefficient matrix is interpreted. For example, the inflation due to using PCA could cause a pattern coefficient to become large enough to be considered salient when it otherwise would be considered a nonsalient pattern coefficient. When cross-loading occurs, it is difficult to determine which factor a pattern coefficient belongs to and this may cause an important variable to be eliminated. When best practices are not followed, the results can be ambiguous, interpretable, and/or flawed. Finally, Preacher and MacCallum (2003) indicate that PCA with varimax rotation would yield similar results to common factor analysis when the communalities are high and if the latent variables are practically uncorrelated; otherwise, PCA with varimax rotation is likely to yield distorted results.

EFA is used to explore the potential constructs underlying a measure and one of the best ways to ascertain the latent structure of an instrument is to use multiple methods to see which set provides the best interpretation of the data. Some researchers may feel using multiple methods is akin to “data mining,” but EFA is an exploratory procedure. Therefore, use of multiple methods is not data mining and is, in fact, the proper way to conduct an EFA (Thompson, 2004). Moreover, researchers need to expand the procedures used to retain factors beyond the eigenvalue-greater-than-one rule and the scree plot. Of the analyses reviewed, the majority relied on either the eigenvalue-greater-than-one rule or the scree test in isolation or used a combination of the two to determine how many factors to retain. Both methods can lead to retaining too many or too few factors. The eigenvalue-greater-than-one rule is simple and objective, but when two factors have eigenvalues of 1.01 and .99, respectively, one is retained and the other rejected even though the factors are explaining approximately the same amount variance (Thompson, 2004). With the scree test, two people looking at the same scree plot may decide to retain two different numbers of factors; this could result in retaining too many or too few factors. When too many or too few factors are retained, the factor structure becomes very difficult to interpret and can contribute to a misinterpretation of the latent factors. Using multiple methods will help researchers determine the optimal number of factors to retain. For example, factor retention procedures should use the eigenvalue-greater-than-one rule, scree tests, and empirically based methods like parallel analysis (Kahn, 2006).

Another area for improvement is in the reporting of the matrix used to analyze the data, the correlations between factors, the factor pattern coefficient matrix, the normality statistics and the factor structure coefficient matrix if using an oblique rotation. All data associated with an EFA (e.g., matrix
of association, pattern coefficients, structure coefficients) should be provided within the text, in tables or as an appendix (or as supplemental information), because this information helps readers to judge the quality of the EFA (Kahn, 2006). However, a large portion of studies reviewed did not provide this critical information. For example, 90% of the analyses did not provide access to the matrix used to analyze the data, 33% did not include the factor pattern coefficient matrix, 97% did not provide information on skewness and kurtosis and none of the studies using an oblique rotation reported the factor structure coefficient matrix. This knowledge provides readers with the necessary information to judge the EFA, the interpretations, and the conclusions reached. Accurate judgments cannot be reached without this information. This is especially true for oblique rotation because both the factor pattern and structure coefficients matrices need to be consulted to make accurate decisions (Kahn, 2006; Thompson, 2004).

Our results are similar to those obtained by Fabrigar et al. (1999), who observed that “... In more than half of all factor analyses reviewed, information was not provided concerning at least one of the decisions” (p. 293). The lack of complete details about the analytic procedures used is a concern in EFA research because the reader has to trust that the EFA was conducted competently (Norris & Lecavalier, 2010). Two potential reasons why researchers underreport valuable information may be the reliance on methods and reporting habits of previously published articles that used questionable methods and questionable reporting habits, and authors may not be as knowledgeable about EFA because few receive formal training in factor analysis (Fabrigar et al., 1999). Openness and transparency are priorities in reporting an EFA. Although researchers followed some of the recommended guidelines with greater frequency, we recommend researchers report all information related to the EFAs they conduct.

EFA is an exploratory method and the subsequent results and interpretation are highly dependent upon the a priori choices of researchers. With detailed information about the rationale, reasoning, and methods, readers will better understand the results and their meaning. Guidelines for best practices compel authors to think critically about the choices they will make, increase the value of the resulting information, and increase the overall quality of factor analytic research, generally (Worthington & Wittaker, 2006).

The current study is not without limitations. Because the analyses were taken from a single journal, the results are limited to studies published in RP. However, the results coincide with previous studies of EFA methods and reporting practices (e.g., Henson & Roberts, 2006). Future research in this area could include other journals relevant to rehabilitation psychologists (e.g., Archives of Physical Medicine and Rehabilitation, Disability and Rehabilitation). Another limitation is the reliance on descriptive statistics. Consistent with previous studies of this nature, we did not use statistical test of significance to evaluate the data. Furthermore, it is possible that an article using an EFA published between 1999 and April 2014 was not included in the sample. The consistency and accuracy of future research studies of this type may be increased by using raters with expertise in EFA.

In conclusion, in the context of previous critiques of published EFAs, the present study indicates that researchers who publish in RP appear to comply with best practices by using adequate sample sizes, using multiple methods, and by specifying the extraction and rotation methods used. Compared to other published reviews, the quality of EFA studies in RP may be considered above average. Future EFA studies should continue to observe recommended guidelines by reporting the type of extraction and rotation methods used, and the methods used to retain factors and by using multiple methods (e.g., extraction, rotation, factor retention). Researchers should also report the matrix used to conduct the analysis, the normality statistics, the factor pattern coefficient matrix and when applicable the factor structure coefficient matrix and the correlation among factors. The reporting of complete details about all the choices made when conducting an EFA is strongly recommended. Most importantly, researchers need to be aware of the proper use of principal component analysis and common factor analysis and the potential negative consequences of relying on PCA with varimax rotation in the wrong research context.

References


Appendix A
Exploratory Factor Analysis: Basic Concepts

<table>
<thead>
<tr>
<th>Concept</th>
<th>Explanation of concept</th>
<th>Reference</th>
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<tbody>
<tr>
<td>Latent variables or unobserved variables</td>
<td>Latent variables are variables that we cannot measure directly. For example, depression is a latent variable because we cannot measure it directly. We can infer the presence of depression from scores on a measure of depression. Exploratory factor analysis provides a method to make inferences about latent variables.</td>
<td>Thompson (2004)</td>
</tr>
<tr>
<td>Observed variables</td>
<td>Observed variables are variables we can measure. We cannot measure depression directly, but we can measure how sad you are feeling, which we can use as a reflection of depression.</td>
<td>Thompson (2004)</td>
</tr>
<tr>
<td>Data reduction</td>
<td>Data reduction is taking a set of variables and reducing it to the smallest set of variables, while retaining as much of the variance as possible. For example, a data reduction technique like principal component analysis can take a data set containing 20 variables related to cognitive development and reduce it to 10 variables while still being able to explain a similar amount of variance as the 20 variables.</td>
<td>Gorsuch (1983)</td>
</tr>
<tr>
<td>Matrix of association</td>
<td>The matrix of association is the type of matrix used to conduct an EFA. Most commonly, it is a correlation or covariance matrix.</td>
<td>Thompson (2004)</td>
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<table>
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<tr>
<th>Concept</th>
<th>Explanation of concept</th>
<th>Reference</th>
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<tr>
<td>Extraction</td>
<td>Factor extraction is the method by which the latent variables of interest are generated. There are wide varieties of extraction methods, and each method represents a different mathematical algorithm. In the simplest math, the latent variables in EFA (also known as factors) are the product between an extraction method and the matrix of association. During the extraction, factors are generated one at a time. The first factor accounts for the most variance and each subsequent factor accounts for less and less variance. This is why it is important to retain the right number of factors. Retaining too many factors causes the retention of factors that do not explain meaningful variance.</td>
<td>Steger (2006); Thompson (2004)</td>
</tr>
<tr>
<td>Pattern coefficients</td>
<td>Pattern coefficients are the weights applied to EFA and are commonly referred to as factor loadings. They are analogous to the beta weights in regression analysis. The pattern coefficient can be evaluated in the same manner as a Pearson correlation.</td>
<td>Kahn (2006); Thompson (2004)</td>
</tr>
<tr>
<td>Factor pattern coefficient matrix</td>
<td>The factor pattern coefficient matrix is the matrix that contains all the pattern coefficients for each latent variable and measured variable pair.</td>
<td>Kahn (2006); Thompson (2004)</td>
</tr>
<tr>
<td>Structure coefficients</td>
<td>Structure coefficients are the Pearson correlation between measured variables and latent variables.</td>
<td>Kahn (2006); Thompson (2004)</td>
</tr>
<tr>
<td>Factor structure coefficient matrix</td>
<td>The factor structure coefficient matrix is the matrix containing all the correlations between the latent variables and the measured variables.</td>
<td>Kahn (2006); Thompson (2004)</td>
</tr>
<tr>
<td>Rotation</td>
<td>Rotation takes place after the latent variables or factors are extracted. Factor rotation is a method to help to improve the interpretability of the latent variables. Without factor rotation, it would be nearly impossible to determine which pattern coefficients are most closely associated with which latent variables. There are many different rotation methods, and each one represents a different mathematical algorithm. In simple terms, rotated latent variables are the product between the extracted latent variables and a rotation method.</td>
<td>Browne (2001); Thompson (2004)</td>
</tr>
<tr>
<td>Orthogonal rotation</td>
<td>Orthogonal rotation is the name for a broad category of different types of rotation methods, where there is an assumption of a zero correlation between latent variables or factors. Varimax and equimax are the two most popular types of orthogonal rotation.</td>
<td>Browne (2001); Thompson (2004)</td>
</tr>
<tr>
<td>Oblique rotation</td>
<td>Oblique rotation is the name for a broad category of different types of rotation methods, where there is an assumption that the latent variables are correlated. Two of the more popular oblique rotations are promax and direct oblimin.</td>
<td>Browne (2001); Thompson (2004)</td>
</tr>
<tr>
<td>Eigenvalue</td>
<td>An eigenvalue is a mathematical quantity reflecting the amount of variance associated with a factor before it is rotated.</td>
<td>Reise, Waller, and Comrey (2000); Thompson (2004)</td>
</tr>
<tr>
<td>Eigenvalue-greater-than-one rule (Guttman–Kaiser criterion)</td>
<td>This rule means that only latent variables or factors that have eigenvalues greater than one are retained for interpretation. This rule is related to the use of principal component analysis, where each observed variable under investigation accounts for one eigenvalue. Therefore, it is not functional to include latent variables or factors that accounts for less variance than a single observed variable.</td>
<td>Reise, Waller, and Comrey (2000); Thompson (2004)</td>
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<tr>
<th>Concept</th>
<th>Explanation of concept</th>
<th>Reference</th>
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<tbody>
<tr>
<td>Scree test</td>
<td>The scree test is a method for determining how many latent variables or factors to retain. The scree test is completed by examining a scree plot. The x-axis contains the factor numbers and the y-axis represents the eigenvalues. When factors are extracted, they have a corresponding eigenvalue and factor number and those pairs are plotted. There are several ways to interpret a scree plot. One way is to find the point on the scree plot where the values start to level off, and that point will be the number of factor to retain. Because the scree test is a subjective method, different cutoffs should be used to see which number of factors best fits the data. In the example below, we would check whether 3, 4, or 5 factors provide the optimal number of factors.</td>
<td>Cattell (1966)</td>
</tr>
<tr>
<td>Parallel analysis</td>
<td>Parallel analysis is a method for determining how many latent variables or factors to retain. There are syntax files available for running a parallel analysis. In this method, the original data is randomized in order to create a new scree plot. The new scree plot is compared to the scree plot of the original data to see where the plots cross. The number of factors retained is determined by point where the random data eigenvalues exceed the eigenvalues for the original data. The factor number to the left of the inflection point is how many factors are retained. In the example below, the solid line represents the original data and we would conclude there are three factors with the possibility for a fourth factor.</td>
<td>Hayton, Allen, and Scarpello (2004)</td>
</tr>
<tr>
<td>Interfactor correlations</td>
<td>Interfactor correlations are the correlations between latent variables or factors. These correlations are automatically generated when an oblique rotation is selected.</td>
<td>Thompson (2004)</td>
</tr>
<tr>
<td>Communalities</td>
<td>The communalities are the amount of variance that each observed variable accounts for after extraction. This is calculated by squaring the pattern coefficients and summing them across factors. A low communality means that the specific observed variable has little overlap with the factors and is not explaining a salient amount of variance. For a high communality, the opposite is true.</td>
<td>Thompson (2004)</td>
</tr>
<tr>
<td>Cross-loading</td>
<td>Cross-loading is a situation where one observed variable has high pattern coefficients on two or more factors. When this happens, it is difficult to decide which latent variable or factor the observed variable belongs.</td>
<td>Thompson (2004)</td>
</tr>
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</table>

Note. EFA = exploratory factor analysis.