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Exploratory factor analysis: A five-step guide for novices

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Abstract
Factor analysis is a multivariate statistical approach commonly used in psychology, education, and more recently in the health-related professions. This paper will attempt to provide novice researchers with a simplified approach to undertaking exploratory factor analysis (EFA). As the paramedic body of knowledge continues to grow, indeed into scale and instrument psychometrics, it is timely that an uncomplicated article such as this be offered to the paramedic readership both nationally and internationally. Factor analysis is an important tool that can be used in the development, refinement, and evaluation of tests, scales, and measures that can be used in education and clinical contexts by paramedics. The objective of the paper is to provide an exploratory factor analysis protocol, offering potential researchers with an empirically-supported systematic approach that simplifies the many guidelines and options associated with completing EFA.

Keywords: confirmatory factor analysis; exploratory factor analysis

Introduction
Historically factor analysis was used primarily by psychology and education; however its use within the health science sector has become much more common during the past two decades.[1] This increase is illustrated in recent surveys of health science electronic databases, where articles reporting factor analysis increased by 16,000% (2 articles in 1985 to 326 articles in 2000).[1] Applying a similar electronic database search involving paramedic articles only yielded one article utilising factor analysis.[2] While this finding perhaps is not surprising, the paramedic body of knowledge and application of multivariate statistics is likely to increase with the passage of time, particularly as many paramedics opt to pursue postgraduate studies.

While statistical software and personal computers make analysing data easier and more accessible, underpinning statistical knowledge of measurement theory is not as straightforward, and is a current weakness not only of paramedic graduate programs, but across many other cognate health care disciplines. Kline (1994), cited in Pett et al[1, p.10] adds,

> *"With the advent of powerful computers and the dreaded statistical packages which go with them, factor analysis and other multivariate methods are available to those who have never been trained to understand them".*

Therefore the aim of this paper is to present a factor analysis protocol with the intention of educating kindred paramedic educators, postgraduate students, and researchers who may undertake research requiring such an approach.

Seven points will be discussed:

1) an overview of factor analysis
2) types of factor analysis
3) the suitability of data for factor analysis
4) how factors can be extracted from data
5) what determines factor extraction
6) types of rotational methods, and
7) interpretation and construct labelling. A five-step factor analysis will be presented.

What is Factor Analysis?
While factor analysis has origins dating back 100 years through the work of Pearson[3] and Spearman,[4] the practical application of this approach has been suggested to be in fact a modern occurrence. As Kieffer (1999), cited in Henson and Roberts[5, p.2] noted,

> *"Spearman, through his work on personality theory, provided the conceptual and theoretical rationale for both exploratory and confirmatory factor analysis. Despite the fact that the conceptual bases for these methods have been available for many decades, it was not until the wide-spread availability of both the computer and modern statistical software that these analytic techniques were employed with any regularity".*

Factor analysis is commonly used in the fields of psychology and education[6] and is considered the method of choice for interpreting self-reporting questionnaires.[7] Factor analysis is a multivariate statistical procedure that has many uses,[8-11] three of which will be briefly noted here. Firstly, factor analysis reduces a large number of variables into a smaller set of variables (also referred to as factors). Secondly, it establishes underlying dimensions between measured variables and latent constructs, thereby allowing the formation and refinement of theory. Thirdly, it provides construct validity evidence of self-reporting scales. Nunnally (1978), cited by Thompson[11, p.5] adds,

> *"… factor analysis is intimately involved with questions of validity … Factor analysis is at the heart of the measurement of psychological constructs".*

Table 1. Objectives of Exploratory Factor Analysis[1,11]

• Reduce the number of variables
• Examine the structure or relationship between variables
• Detection and assessment of unidimensionality of a theoretical construct
• Evaluates the construct validity of a scale, test, or instrument
• Development of parsimonious (simple) analysis and interpretation
• Addresses multicollinearity (two or more variables that are correlated)
• Used to develop theoretical constructs
• Used to prove/disprove proposed theories

Types of Factor Analysis

There are two major classes of factor analysis: Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA). Broadly speaking EFA is heuristic. In EFA, the investigator has no expectations of the number or nature of the variables and as the title suggests, is exploratory in nature. That is, it allows the researcher to explore the main dimensions to *generate* a theory, or model from a relatively large set of latent constructs often represented by a set of items.[1,5,11,12] Whereas, in CFA the researcher uses this approach to *test* a proposed theory (CFA is a form of structural equation modelling), or model and in contrast to EFA, has assumptions and expectations based on priori theory regarding the number of factors, and which factor theories or models best fit.

It is important to note that factor analysis as a statistical approach is not without controversy or criticism, although according to Thompson most of these criticisms apply themselves to EFA rather than CFA.[11] These criticisms are largely based on the subjectiveness of the results which are determined by the researcher,[5] as cited by Cronkhite and Liska (1980), in Thompson:[11, p.106]

> *"Apparently, it is so easy to find semantic scales which seem relevant to [information] sources, so easy to name or describe potential/hypothetical sources, so easy to capture college students to use the scales to rate the sources, so easy to submit those rates to factor analysis, so much fun to name the factors when one's research assistant returns with the computer printout, and so rewarding to have a guaranteed publication with no fear of nonsignificant results that researchers, once exposed to the pleasures of the factor analytic approach, rapidly become addicted to it".*

Tabachnick and Fidell[10, p.611] also address the limitations of EFA, noting that "decisions about number of factors and rotational scheme are based on pragmatic rather that theoretical criteria", as also Henson RK and Roberts JK[5] claim, that to limit the subjectiveness of EFA, the researcher must be systematic, thoughtful, and apply sound judgement to latent variables and factor reduction and construction.

The Five-Step Exploratory Factor Analysis Protocol

Despite EFA being a seemingly complex statistical approach, the approach taken in the analysis is in fact sequential and linear, involving many options.[11] Therefore, developing a protocol or decision pathway is crucial in potential oversights (see Thompson,[11, Ch.3] Pallantt,[26 , Ch.15] and Pett et al.[1, Ch.1] for examples in other EFA protocols). The following Five-Step Exploratory Factor Analysis Protocol (see Figure 1) provides novice researchers with starting reference point in developing clear decision pathways. Each of these steps will be now explained in more detail.

Throughout the paper, where applicable, examples of Statistical Program for Social Sciences (SPSS) output have been included. It is important to note that we have not used the same data source in each example, hence why different factor solutions are presented. It is also important to note that SPSS as a statistical program is revised on a regular basis; hence the format of the results generated with more contemporary versions of SPSS may vary slightly.

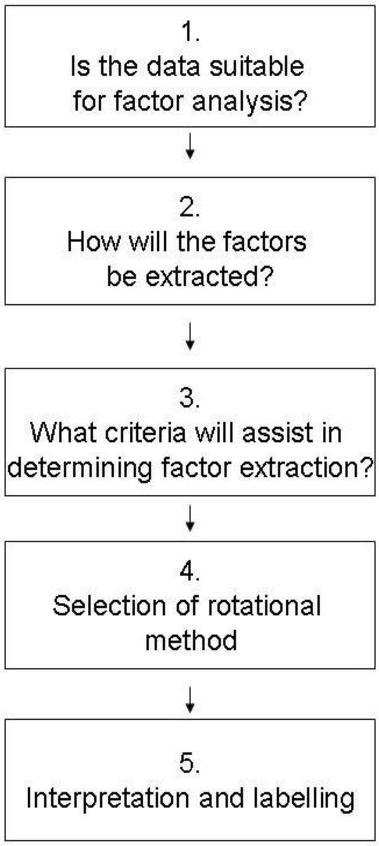

Figure 1. The 5-step Exploratory Factor Analysis Protocol

Step 1: Is the data suitable for factor analysis?

Sample Size

Although sample size is important in factor analysis, there are varying opinions, and several guiding rules of thumb are cited in the literature.[6,8-10] The lack of agreement is noted by Hogarty et al.,[6, p.203] who stated that these "disparate [sample size] recommendations have not served researchers well". General guides include, Tabachnick's rule of thumb[10] that suggests having at least 300 cases are needed for factor analysis. Hair et al[9] suggested that sample sizes should be 100 or greater. A number of textbooks[1,8-10] cite the work of Comrey and Lee[13] in their guide to sample sizes: 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 or more as excellent.

According to MacCallum, Widaman, Zhang, and Hong (1999), cited in Henson and Roberts[5] such rules of thumb can at times be misleading and often do not take into account many of the complex dynamics of a factor analysis. "They illustrated that when communalities are high (greater than .60) and each factor is defined by several items, sample sizes can actually be relatively small".[5, p. 402] Others such as Guadagnoli and Velicer found that solutions with correlation coefficients >.80 require smaller sample sizes,[14] while Sapnas and Zeller[15] point out that even 50 cases may be adequate for factor analysis. As can be seen, the suggested sample size required to complete a factor analysis of a group of items that participants have responded to, varies greatly.

Sample to Variable Ratio (*N:p* ratio)
Another set of recommendations also exist providing researchers with guidance regarding how many participants are required for each variable, often termed, the sample to variable ratio, often denoted as *N:p* ratio where *N* refers to the number of participants and *p* refers to the number of variables.[6] The same disparate recommendations also occur for sample to variable ratios as they do for determining adequate sample sizes.[6,9] For example, rules of thumb range anywhere from 3:1, 6:1, 10:1, 15:1, or 20:1.[1,8-10,16] To highlight this ambiguity, investigators such as Hogarty et al. and MacCallum et al. have undertaken studies to test these guides.[6,17] Hogarty et al.[6, p.222] noted that, "our results show that there was not a minimum level of *N* or *N:p* ratio to achieve good factor recovery across conditions examined".

Factorability of the correlation matrix
A correlation matrix should be used in the EFA process displaying the relationships between individual variables. Henson and Roberts[5] pointed out that a correlation matrix is most popular among investigators. Tabachnick and Fidell[10] recommended inspecting the correlation matrix (often termed Factorability of *R*) for correlation coefficients over 0.30. Hair et al. (1995) categorised these loadings using another rule of thumb as ±0.30=minimal, ±0.40=important, and ±.50=practically significant.[9] If no correlations go beyond 0.30, then the researcher should reconsider whether factor analysis is the appropriate statistical method to utilise.[9,10] In other words a factorability of 0.3 indicates that the factors account for approximately 30% relationship within the data, or in a practical sense, it would indicate that a third of the variables share too much variance, and hence becomes impractical to determine if the variables are correlated with each other or the dependent variable (multicollinearity).

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy/Bartlett's Test of Sphericity
Prior to the extraction of the factors, several tests should be used to assess the suitability of the respondent data for factor analysis. These tests include Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy,[18,19] and Bartlett's Test of Sphericity.[20] The KMO index, in particular, is recommended when the cases to variable ratio are less than 1:5. The KMO index ranges from 0 to 1, with 0.50 considered suitable for factor analysis.[9,10] The Bartlett's Test of Sphericity should be significant (p<.05) for factor analysis to be suitable.[9,10] Examples are shown in Table 2.

Table 2: Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity *(SPSS Output)*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.536
Bartlett's Test of Sphericity	Approx. Chi-Square	2582.571
	Df	1225
	Sig.	.000

Step 2: How will the factors be extracted?
The aim of rotation is to simplify the factor structure of a group of items, or in other words, high item loadings on one factor and smaller item loadings on the remaining factor solutions.[21] There are numerous ways to extract factors: Principal components analysis

(PCA), principal axis factoring (PAF), image factoring, maximum likelihood, alpha factoring, and canonical.[10,11] The most common extraction methods are listed in Table 3.

Table 3. Extraction methods commonly used in factor analysis (EFA and CFA)[1]

- Principal components analysis (PCA)
- Principal axis factoring (PAF)
- Maximum likelihood
- Unweighted least squares
- Generalised least squares
- Alpha factoring
- Image factoring

However, PCA and PAF are used most commonly in the published literature.[5,10,11] The decision whether to use PCA and PAF is fiercely debated among analysts,[5] although according to Thompson the practical differences between the two are often insignificant, particularly when variables have high reliability,[11] or where there are 30 or more variables.[8] Thompson noted that PCA is the default method in many statistical programs, and thus, is most commonly used in EFA.[11] However, PCA is also recommended when no priori theory or model exists.[8] Pett et al. (2003) suggested using PCA in establishing preliminary solutions in EFA.[1]

Step 3: What criteria will assist in determining factor extraction?

The aim of the data extraction is reduce a large number of items into factors. In order to produce scale unidimensionality, and simplify the factor solutions several criteria are available to researchers. However, given the choice and sometimes confusing nature of factor analysis, no single criteria should be assumed to determine factor extraction.[21] This is reinforced by Thompson and Daniel[22, p.200] who stated that the "simultaneous use of multiple decision rules is appropriate and often desirable". Hair et al. point out that the majority of factor analysts typically use multiple criteria.[9] Many extraction rules and approaches exist including: Kaiser's criteria (eigenvalue > 1 rule),[23] the Scree test,[24] the cumulative percent of variance extracted, and parallel analysis.[25] It is suggested that multiple approaches be used in factor extraction. For instance, many peer-reviewed educational and psychological measurement journals now request that multiple extraction techniques are used for a manuscript to be accepted for publication.

Cumulative Percentage of Variance and Eigenvalue > 1 Rule

Cumulative percentage of variance (criterion) is another area of disagreement in the factor analysis approach, particularly in different disciplines, for example, the natural sciences, psychology, and the humanities.[5] No fixed threshold exists, although certain percentages have been suggested. According to Hair et al.[9] in the natural sciences, factors should be stopped when at least 95% of the variance is explained. In the humanities, the explained variance is commonly as low as 50-60%.[1,9] The example below in Table 4 demonstrates a cumulative percentage of variance of 40.6% and a total of 7 components (factors) having an eigenvalue > 1.

Table 4: Total Variance Explained *(SPSS Output).*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	19.095	40.627	40.627	19.095	40.627	40.627
2	2.644	5.625	46.252	2.644	5.625	46.252
3	1.733	3.688	49.940	1.733	3.688	49.940
4	1.354	2.882	52.822	1.354	2.882	52.822
5	1.156	2.459	55.281	1.156	2.459	55.281
6	1.144	2.433	57.714	1.144	2.433	57.714
7	1.014	2.158	59.873	1.014	2.158	59.873

Extraction Method: Principal Component Analysis.

Scree Test

As noted by Gorsuch,[8] Tabachnick and Fidell,[10] and Thompson,[11] interpreting Scree plots is subjective, requiring researcher judgement. Thus, disagreement over which factors should be retained is often open for debate.[1] Although this disagreement and subjectiveness is reduced when sample sizes are large, *N:p* ratios are (>3:1) and communalities values are high.[1,8] The 'Scree Test' was given its name by Cattell[24] due to the Scree Test graphical presentation, which has visual similarities to the rock debris (Scree) at the foot of a mountain.

Inspecting and interpretation of a Scree plot involves two steps:

1. Draw a straight line through the smaller eigenvalues where a departure from this line occurs. This point highlights where the debris or break occurs. (If the Scree is messy, and difficult to interpret, additional manipulation of data and extraction should be undertaken).

2. The point above this debris or break (not including the break itself) indicates the number of factors to be retained.

In the example below (see Figure 2), the inspection of the Scree plot and eigenvalues produced a departure from linearity coinciding with a 6-factor result. Therefore this Scree Test indicates that the data should be analysed for 6 factors.

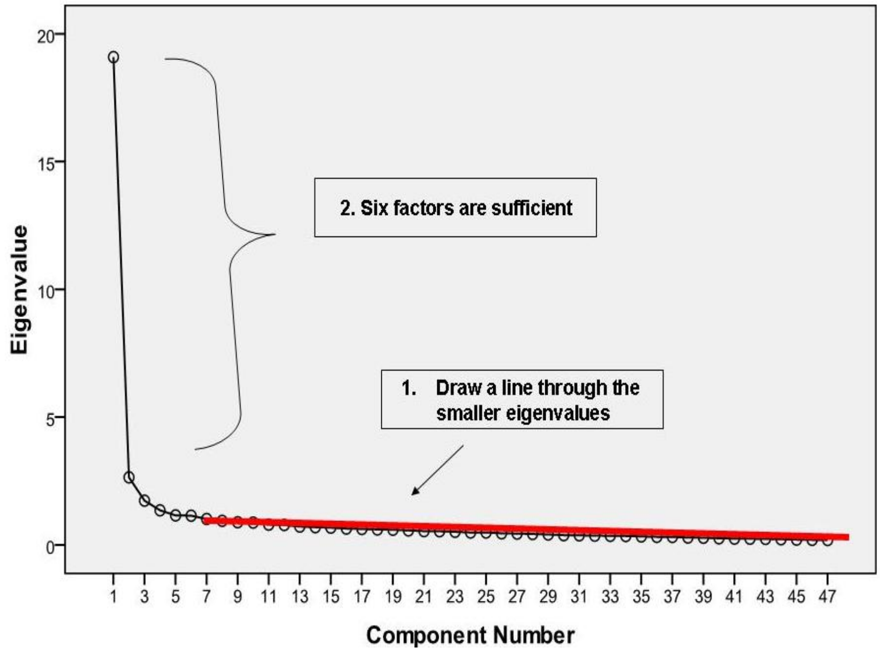

Figure 2: Scree Test Criterion *(SPSS Output)*

Parallel Analysis
Parallel analysis is an under-used factor extraction technique[5] and is often not reported in the literature. One possible reason for limited use is the analysis is not available in conventional statistical programs such as SPSS or SAS.[22] However, authors suggest that parallel analysis has both merit and application in extracting factors.[5,22] Thompson[11, p.34] adds, "… parallel analysis appears to be among the best methods for deciding how many factors to extract or retain".

In parallel analysis, actual eigenvalues are compared with random order eigenvalues. Factors are retained when actual eigenvalues surpass random ordered eigenvalues. In the example below (see Table 5) only 3 of the 13 originally generated factors are retained.

Table 5: Parallel Analysis *(Monte Carlo PA Output)* (adapted from)[26]

Component Number	Actual eigenvalue from PCA	Random order from parallel analysis	Decision
1	14.947	3.2670	Accept
2	4.714	3.0052	Accept
3	3.025	2.8050	Accept
4	2.312	2.6318	Reject
5	2.204	2.4668	Reject
6	1.940	2.3386	Reject
7	1.893	2.2110	Reject
8	1.546	2.0936	Reject
9	1.375	1.9715	Reject
10	1.287	1.8606	Reject
11	1.265	1.7701	Reject
12	1.133	1.6712	Reject
13	1.020	1.5861	Reject

Following these analyses a final number of factors or best-fit solution will be presented. At this point the researcher will require careful and thoughtful judgement on which solution is the best-fit and which of the factors extracted make the most conceptual sense.

Step 4: Selection of Rotational Method

Another consideration when deciding how many factors you will analyse your data is whether a variable might relate to more than one factor. Rotation maximises high item loadings and minimises low item loadings, therefore producing a more interpretable and simplified solution. There are two common rotation techniques: orthogonal rotation and oblique rotation. Researchers have several methods to choose from both rotation options, for example, orthogonal varimax/quartimax or oblique olbimin/promax. Orthogonal Varimax rotation first developed by Thompson[11] is the most common rotational technique used in factor analysis,[11] which produce factor structures that are uncorrelated.[21] In contrast, oblique rotation produce factors that are correlated, which is often seen as producing more accurate results for research involving human behaviours, or when data does not meet priori assumptions.[21] Regardless of which rotation method is used, the main objectives are to provide easier interpretation of results, and produce a solution that is more parsimonious.[9,27]

As suggested by Pett, Lackey, and Sullivan,[1] and Kieffer,[27] following PCA analysis, PAF should also be examined for comparison and assessment for best fit. In other words, whichever rotated solution produces the best fit and factorial suitability, both intuitively and conceptually, should be used. Once this has been assessed, the researcher then examines items that do not load or are unable to be assigned to a factor using the above guides and makes a decision whether the items should be discarded. For example, the item might load on several factors, not load on any factors, or simply not conceptually fit any logical factor structure.

Step 5: Interpretation

Interpretation involves the researcher examining which variables are attributable to a factor, and giving that factor a name or theme. For example, a factor may have included five variables which all relate to pain perception; therefore the researcher would create a label of “pain perception” for that factor. Traditionally, at least two or three variables must load on a factor so it can be given a meaningful interpretation.[5,28] The labelling of factors is a subjective, theoretical, and inductive process.[1] Henson and Roberts (2006) note “the meaningfulness of latent factors is ultimately dependent on researcher definition”.[5, p.396] The reason for thorough and systematic factor analyses is to isolate items with high loadings in the resultant pattern matrices. In other words, it is a search to find those factors that taken together explain the majority of the responses. In the presented example in Table 6, seven factors have been produced. If the researcher is content with these factors, these should then be operationalised and descriptively labelled. It is important that these labels or constructs reflect the theoretical and conceptual intent.

Table 6

	Component						
	1	2	3	4	5	6	7
Item 1	.717						
Item 2	.703						
Item 3	.639						
Item 4	.627						
Item 5	.564						
Item 6	.563						
Item 7	.547						
Item 8	.485						
Item 9	.482						
Item 10	.451						
Item 11							
Item 12							
Item 13		.754					
Item 14		.637					
Item 15		.587					
Item 16		.584					
Item 17		.583					
Item 18		.568					
Item 19		.524					
Item 20		.516					
Item 21							
Item 22			.607				
Item 23			.551				
Item 24			.528				
Item 25			.523				
Item 26			.495				
Item 27							
Item 28							
Item 29		.466		.557			
Item 30				.552			
Item 31				.532			
Item 32				.504			
Item 33				.489			
Item 34							
Item 35					.688		
Item 36					.627		
Item 37					.598		
Item 38					.538		
Item 39					.515		
Item 40						.674	
Item 41						.636	
Item 42						.611	
Item 43							.698
Item 44							.559
Item 45							.518
Item 46							.492

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Conclusion

Exploratory factor analysis is a complex multivariate statistical approach involving many linear and sequential steps. In addition, many options and rules of thumb apply themselves to EFA emphasising that clear decision sequencing and protocols are paramount in each investigation. The intention of the paper is to provide the paramedic readership with a user-friendly guide to exploratory factor analysis. It is hoped the Five-step Exploratory Factor Analysis Protocol will be useful (and make research less daunting) in those contemplating undertaking research requiring this statistical technique.

Examples of published EFA

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Hoban JD, Lawson SR, Mazmanian PE, Best AM, Seibel HR. The Self-Directed Learning Readiness Scale: a factor analysis study. Medical Education. 2005;39(4):370-9.

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