Exploratory Factor Analysis; Concepts and Theory

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Abstract: - Exploratory factor analysis is a complex and multivariate statistical technique commonly employed in information system, social science, education and psychology. This paper intends to provide a simplified collection of information for researchers and practitioners undertaking exploratory factor analysis (EFA) and to make decisions about best practice in EFA. Particularly, the objective of the paper is to provide practical and theoretical information on decision making of sample size, extraction, number of factors to retain and rotational methods.

Key-Words: - Factor Analysis, Exploratory Factor Analysis, Factor Retention Decisions, Scale Development, Extraction and Rotation Methods.

1 Introduction

Factor analysis is a significant instrument which is utilized in development, refinement, and evaluation of tests, scales, and measures (Williams, Brown et al. 2010). Exploratory factor analysis (EFA) is widely used and broadly applied statistical approach in information system, social science, education and psychology. Recently, exploratory factor analysis was applied for a wide range of applications, including finding relationships between socioeconomic, land use, activity participation variables and travel patterns (Pitombo, E.Kawamoto et al. 2011), developing an instrument for the evaluation (Lovett and Zeiss 2002), assessment of services quality dimensions of Internet retailing (Yang, Peterson et al. 2003), e-commerce service quality (Cox and Dale 2001), evaluation of animal movement (Brillinger, Preisler et al. 2004), Intranet adoption (Tang 2000), assessing the motivation (Morris 2001), survey instrument to examine consumer adoption of broadband (Dwivedi, Choudrie et al. 2006), and determining what types of services should be offered to college students (Majors and Sedlacek 2001).

A survey in PsycINFO yielded over 1700 studies that used some form of EFA. Over fifty percent used the varimax rotation for principal components analysis as the approach used for data analysis, and also the majority of the researches used the Kaiser criterion (all factors with eigenvalues greater than one) as a method for deciding the number of constructs to be retained for rotation although it will not always yield the best results for a particular data set (Costello and Osborne 2005).

Thus, the goal of this study is to discuss about exploratory factor analysis protocol and provide practical information for researcher and practitioners. Particularly, below points will be discussed:

1) An overview of exploratory factor analysis,
2) Sample size,
3) Factor extraction methods,
4) Number of factors to retain techniques,
5) Types of rotational methods

2 Factor Analysis

Factor analysis (FA) has origins dating back 100 years through the work of Pearson and Spearman (Spearman 1904). Factor analysis as a multivariate statistical procedure, is commonly utilized in the fields of information system, psychology, commerce and education and is considered the approach of choice for interpreting self-reporting survey (Byrant, Yarnold et al. 1999).

FA reduces a large number of variables (factors) into a smaller set. Furthermore, it establishes underlying dimensions between measured factors and latent constructs, thereby allowing the formation and refinement of theory. Moreover, it provides construct validity evidence of self-reporting scales (Gorsuch 1983; Hair, Anderson et al. 1995a; Tabachnick and Fidell 2001; Thompson 2004).

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3 Types of Factor Analysis

Factor analysis is divided to two main categories namely; Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA) (Williams, Brown et al. 2010). While the researcher has no expectations of the number or nature of the factors, EFA is used. As the title suggests, it allows the investigator to explore the main variables to create a theory, or model from a relatively large set of latent dimensions often represented by a set of items (Pett, Lackey et al. 2003; Swisher, Beckstead et al. 2004; Thompson 2004; Henson and Roberts 2006). Whereas, CFA as a form of structural equation modeling (SEM), is applied to test the proposed theory by researcher, or model. CFA, in contrast to EFA, has assumptions and expectations based on priori model and theory about the number of constructs, and which construct theories or models best fit (Williams, Brown et al. 2010).

Although both EFA and CFA methods try to account for as much variance as possible in a set of observed variables with a smaller set of latent variables, factors, or components, EFA is principally suitable for scale development and applied when there is little theoretical basis for specifying a priori the number and patterns of common factors (Hurley, Scandura et al. ; Hayton, Allen et al. 2004). (Tabachnick and Fidell 2001) also address the limitations of EFA, noting that “decisions about number of factors and rotational scheme are based on pragmatic rather that theoretical criteria”.

4 Exploratory Factor Analyses

Despite exploratory factor analysis being a apparently complex statistical method, the approach taken in the analysis is sequential and linear, involving many options (Thompson 2004). Objectives of Exploratory Factor Analysis (Pett, Lackey et al. 2003; Thompson 2004) are:

- Reduction of number of factors (variables)
- Assessment of multicollinearity among factors which are correlated
- Unidimensionality of constructs evaluation and detection
- Evaluation of construct validity in a survey
- Examination of factors (variables) relationship or structure
- Development of theoretical constructs
- Prove proposed theories

According to (Fabrigar, Wegener et al. 1999), there are five methodological issues that researchers should consider for utilizing EFA. First, researcher should determine if the EFA is the most appropriate statistical method to achieve the purpose of the study. Second, the variables of the study, sample size and nature should be selected. Third, the extraction procedure should be chosen and then determine the method to decide the number of factors to retain. Fifth, researcher need to select the rotation method to yield a final interpretable solution. Failure to make a proper decision about one or more of above mentioned methodological issues may lead to erroneous results and limit the utility of the EFA (Hogarty, Kromrey et al. 2004). Figure one, shows the steps toward implementing exploratory factor analysis.

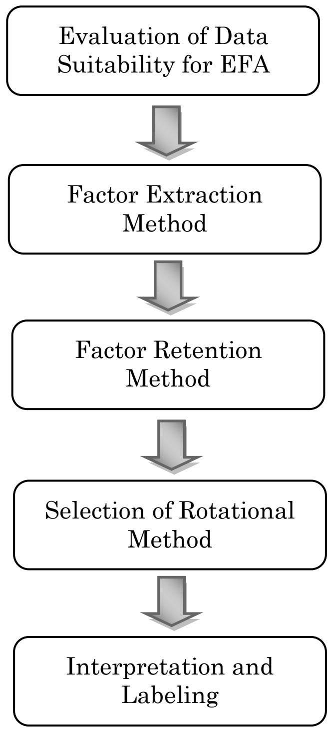

Figure 1: Exploratory Factor Analysis Implementation Steps

4.1 Sample Size

Although sample size is a significant issue FA, there are different ideas and several guiding rules of thumb in the literature (Gorsuch 1983; Tabachnick and Fidell 2001; Hogarty, Hines et al. 2005). This lack of agreement was noted by (Hogarty, Hines et al. 2005) who stated that these “disparate recommendations have not served researchers well”. General guides include (Tabachnick and Fidell 2001)’s rule of thumb that suggests having at least 300 cases are needed for factor analysis. (Hair, Anderson et al. 1995a) suggested that sample sizes should be 100 or greater. (Comrey 1973) stated in

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his guide to sample sizes: 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 or more as excellent. (MacCallum, Widaman et al. 1999) illustrated that when communalities are high (greater than .60) and each factor is defined by several items, sample sizes can actually be relatively small" (Henson and Roberts 2006). Others studies such as (Guadagnoli and Velicer 1988) stated that solutions with correlation coefficients >0.80 require smaller sample sizes while (Sapnas and Zeller 2002) arrgued that even 50 cases may be adequate for factor analysis.

Previous studies revealed that nature of data will determine the adequacy of sample size (Fabrigar, Wegener et al. 1999; MacCallum, Widaman et al. 1999). Commonly, the stronger the data, the smaller the sample can be for an accurate analysis. "Strong data" in factor analysis means uniformly high communalities without cross loadings, plus several variables loading strongly on each factor (Costello and Osborne 2005).

(Costello and Osborne 2005) indicate that if the following problems emerge in the data, a larger sample can help determine whether or not the factor structure and individual items are valid:

1) Item communalities are 0.8 or greater which is known as a "high" (Velicer and Fava 1998) although it is unlikely to happen in real data. More common magnitudes are 0.40 to 0.70 and known as low to moderate communalities. If the item would not be related to other items or additional construct need to be explored, then the item communality will be less than 0.40.

2) (Tabachnick and Fidell 2001) mentioned that instrument items should load at 0.32, which equates to approximately 10% overlapping variance with the other items in that factor. A "crossloading" item is an item that loads at 0.32 or higher on two or more factors. If there are several crossloaders, the items may be poorly written or the a priori factor structure could be flawed (Costello and Osborne 2005). While other researchers (Comery and Lee 1992; Laura J. Burton and Stephanie M. Mazerolle 2011) emphasized 0.50 or higher as a good rule of thumb for the minimum loading of an item with no cross loadings.

3) A construct with fewer than three items is generally weak and unstable; five or more strongly loading items (0.50 or better) are desirable and indicate a solid factor (Costello and Osborne 2005).

4.1.1 Correlation matrix

In EFA, a correlation matrix as one of the most popular statistical technique (Henson and Roberts 2006) is used to determine the relationships between variables. (Tabachnick and Fidell 2001) recommended inspecting the correlation matrix for correlation coefficients over 0.30.

In other words, loading 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) (Williams, Brown et al. 2010).

(Hair, Anderson et al. 1995a) categorised the correlation loadings as 0.30 = minimal, 0.40 = important, and 0.50 = practically. If the correlations is less than 0.30, then it should be reconsidered if FA is proper approach to be used for the research (Hair, Anderson et al. 1995a; Tabachnick and Fidell 2001). If the correlation matrix is an identity matrix (there is no relationship among the items)(Kraiser 1958), EFA should not be applied .

4.1.2 Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Prior to the extraction of the constructs, there are some tests which must be conducted to examine the adequacy of the sample and the suitability of data for FA (Laura J. Burton and Stephanie M. Mazerolle 2011). Sampling adequacy provides the researcher with information regarding the grouping of survey items. Grouping items into a set of interpretable factors can better explain the constructs under investigation. Measures of sampling adequacy evaluate how strongly an item is correlated with other items in the EFA correlation matrix (Laura J. Burton and Stephanie M. Mazerolle 2011).

The sampling adequacy can be assessed by examining the Kaiser-Meyer-Olkin (KMO) (Kaiser 1970). KMO is suggested when the cases to variable ratio are less than 1:5. It ranges from 0 to 1, while according to (Hair, Anderson et al. 1995a; Tabachnick and Fidell 2001), 0.50 considered suitable for FA. On the other hand, (Netemeyer, Bearden et al. 2003) stated that a KMO correlation above 0.60 - 0.70 is considered adequate for analyzing the EFA output.

Bartlett's test of Sphericity (Bartlett 1950) provides a chi-square output that must be significant. It indicates the matrix is not an identity matrix and accordingly it should be significant ($p<.05$) for factor analysis to be suitable (Hair, Anderson et al. 1995a; Tabachnick and Fidell 2001).

In brief, if the KMO indicates sample adequacy and Bartlett's test of sphericity indicates the item correlation matrix is not an identity matrix, then researchers can move forward with the FA (Netemeyer, Bearden et al. 2003).

4.2 Factor Extraction

There are several ways to extract factors: principal components analysis (PCA), principal axis factoring (PAF), image factoring, maximum likelihood, alpha factoring, unweighted least squares, generalised least squares and canonical (Tabachnick and Fidell 2001; Thompson 2004; Costello and Osborne 2005). However, principal components analysis and principal axis factoring are used most commonly in studies (Tabachnick and Fidell 2001; Thompson 2004; Henson and Roberts 2006). The decision whether to use PCA and PAF is fiercely debated among analysts (Henson and Roberts 2006), although the practical differences between the two are often insignificant (Thompson 2004) and according to (Gorsuch 1983), when factors have high reliability or there are thirty or more factors, the is not significant differences.

(Thompson 2004) stated that the reason why PCA is mostly used is that it is the default method in many statistical software. PCA is suggested to be used when no prior theoretical basis or model exists (Gorsuch 1983). Moreover, (Pett, Lackey et al. 2003) recommended using PCA in establishing preliminary solutions in EFA. According to (Costello and Osborne 2005), factor analysis is preferable to principal components analysis which is only a data reduction approach. If researcher have initially developed an instrument with several items and is interested in reducing the number of items , then the PCA is useful (Netemeyer, Bearden et al. 2003).

It is computed without regard to any underlying structure caused by latent variables; components are calculated using all of the variance of the manifest variables, and all of that variance appears in the solution (Ford, MacCallum et al. 1986). When the factors are uncorrelated and communalities are moderate it can produce inflated values of variance accounted for by the components (McArdle 1990; Gorsuch 1997).

Conversely, principle axis factoring is useful while researcher want to determine the underlying factors related to a set of items (Laura J. Burton and Stephanie M. Mazerolle 2011).

On the other hand, (Fabrigar, Wegener et al. 1999) stated that if data are relatively normally distributed, maximum likelihood (ML) is the best choice because "it allows for the computation of a wide range of indexes of the goodness of fit of the model and permits statistical significance testing of factor loadings and correlations among factors and the computation of confidence intervals."

Overall, according to (Costello and Osborne 2005), maximum likelihood or principal axis factoring will give researcher the best results, depending on if data are generally normally-distributed or significantly non-normal, respectively.

4.3 Factor Retention Methods

After extraction phase, the researcher must decide how many constructs to retain for rotation. Factor retention is more important than other phases. (Hayton, Allen et al. 2004) point out three reasons why this decision is so important. First, because there is evidence of robustness across alternatives for these other decisions (Zwick and Velicer 1986). Second, exploratory factor analysis needs to balance parsimony with adequately representing underlying correlations therefore its utility depends on being able to differentiate major factors from minor ones (Fabrigar, Wegener et al. 1999). Also there is conceptual and empirical evidence that both underextraction and overextraction are substantial errors that affect results, although specifying too few is traditionally considered more severe. Both types of misspecifications have been empirically demonstrated to lead to poor factor-loading pattern reproduction and interpretation (Velicer, Eaton et al. 2000; Hayton, Allen et al. 2004) and also they will effect on EFA efficiency and meaning (Ledesma and Valero-Mora 2007).

A number of criteria are available to assist these decisions, but they do not always lead to the same or even similar results (Zwick and Velicer 1986; Thompson and Daniel 1996). Factor retentions methods are; Cumulative percent of variance extracted, Kaiser‟s criteria (eigenvalue > 1 rule) (Kaiser 1960), Scree test (Cattell 1966) and Parallel Analysis (Horn 1965). (Hair, Anderson et al. 1995a) mentioned that the majority of factor analysts commonly use multiple criteria.

4.3.1 Cumulative Percentage of Variance

There is no agreement in cumulative percentage of variance (CPV) in the FA method, particularly in different research area (Henson and Roberts 2006). For instance, in the natural sciences, according to (Hair, Anderson et al. 1995a), factors should be stopped when at least 95% of the variance is

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explained although in the humanities, the explained variance is generally as low as 50-60% (Hair, Anderson et al. 1995a; Pett, Lackey et al. 2003).
There is evidence to suggest that the results of exploratory factor analysis are more accurate when each common factor is represented by multiple variables in the analysis (Williams, Brown et al. 2010). In this regard, (MacCallum, Widaman et al. 1999) posit that when EFA is performed on variables with low communalities substantial distortion in results may occur.

4.3.2 K1 - Kaiser's eigenvalue > 1

According to the K1 - Kaiser's (Kaiser 1960) method, only constructs which has the eigenvalues greater than one should be retained for interpretation. This approach may be the best known and most used in practice (Fabrigar, Wegener et al. 1999) because of its theoretical basis and ease of use (Gorsuch 1983).
Despite the widespread adoption and simplicity of this method, many researchers argued that it is problematic and inefficient. There are three problems using this method for factor retention (Fabrigar, Wegener et al. 1999; Hayton, Allen et al. 2004). Firstly, this approach was proposed for the PCA case, eigenvalues of the correlation matrix with unities at the diagonal and it is not a valid rule in the EFA case, eigenvalues of the correlation matrix with communality estimates at the diagonal (Gorsuch 1983). Secondly, the rule is somewhat arbitrary in that it draws distinctions between factors with eigenvalues just above and just below1 (Fabrigar, Wegener et al. 1999; Hayton, Allen et al. 2004). (Linn 1968) demonstrated that K1 overestimated the correct number of factors by 66%. Lastly, this approach has demonstrated tendency to substantially overestimate the number of factors, and, in some cases, even underestimate them (Horn 1965; Zwick and Velicer 1986). Kaiser himself reported that the number of components retained by K1 is commonly between 1/3, 1/5 or 1/6 the number of variables included in the correlation matrix (Zwick and Velicer 1986). A number of studies have mentioned that K1 is among the least accurate methods for selection of factor retention (Velicer and Jackson 1990; Fabrigar, Wegener et al. 1999; Ledesma and Valero-Mora 2007).

4.3.3 Scree Test

Another popular used method for determining the number of factors to retain is Cattell's Scree test (Cattell 1966) which involves the visual exploration of a graphical representation of the eigenvalues for breaks or discontinuities.
The number of datapoints above the break (not including the point at which the break occurs) is the number of factors to retain. The logic behind this method is that this point divides the important or major factors from the minor or trivial factors (Ledesma and Valero-Mora 2007).
As illustrated by (Gorsuch 1983; Tabachnick and Fidell 2001; Thompson 2004), interpreting Scree plots is subjective, requiring researcher judgment. Therefore, the number of factors to retain and results can be different (Zwick and Velicer 1986; Pett, Lackey et al. 2003). Although this disagreement and subjectiveness is reduced when sample size is large, N:p ratios are (>3:1) and communalities values are high (Linn 1968; Gorsuch 1983; Pett, Lackey et al. 2003).
Nonetheless, (Zwick and Velicer 1986) comparison concluded that the Scree test performed better than the K1 rule, although it was still correct only 57% of the time and in most inaccurate cases, the overestimate of factors has been found (Ledesma and Valero-Mora 2007) even though (Costello and Osborne 2005) noted that Scree test is the best choice for researchers.

4.3.4 Minimum Average Partial

(Velicer 1976) proposed the Minimum Average Partial (MAP), a method which calculates the average of squared partial correlations after each component is partialled out. When the minimum average squared partial correlation is reached, the residual matrix resembles an identity matrix and no further components are extracted (Hayton, Allen et al. 2004).
Based on the nature of this method, the factor which has low loading will not be retained, thus there will be at least two variables with high loading for each retained factor (Zwick and Velicer 1986). According to this property of MAP, it is inaccurate because MAP method consistently underestimated the number of major components for cases that there is low factor loading or low number of variables per factor (Ledesma and Valero-Mora 2007).
Although some researchers (Zwick and Velicer 1986; Wood, Tataryn et al. 1996) argued that MAP has more ability to select the componants compare to CPV, K1 and Scree test. Furthermore, (Zwick and Velicer 1986) stated that MAP is correct in 84% of the time and is the second most accurate method for factor selection.

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4.3.5 Parallel Analysis

Parallel Analysis (PA) has been proposed by (Horn 1965). PA compares the observed eigenvalues extracted from the correlation matrix to be analyzed with those obtained from uncorrelated normal variables. In PA method, the component will be considered important if the eigenvalue actual eigenvalues surpass random ordered eigenvalues (Hayton, Allen et al. 2004; Ledesma and Valero-Mora 2007).

Various researchers point out that Parallel Analysis is the best method to determine how many factors to retain (Humphreys and Montanelli 1975; Zwick and Velicer 1986; Glorfeld 1995) (Thompson and Daniel 1996; Ledesma and Valero-Mora 2007). Besides, (Zwick and Velicer 1986) indicated that Parallel Analysis is correct 92% of the time and it will demonstrate the least variability and sensitivity to different factors.

In brief, it can be concluded that PA is an appropriate method to decide the number of factors to retain in exploratory factor analysis although it is not widely utilized.

4.4 Selection of Rotational Method

An additional issue when researcher decide how many constructs will analyze the data is whether a variable might relate to more than one factor (Williams, Brown et al. 2010). In order to produce a more interpretable and simplified solution, rotation will help by maximizing high item loadings and minimizing low item loadings. Oblique and orthogonal rotations are two types of rotation technique.

Oblique rotation is more accurate while data does not meet priori assumptions (Costello and Osborne 2005). This method allocates the factors to correlate or in other words, producing constructs structures that are correlated. Quartimin, direct oblimin and promax are commonly available methods for oblique rotation.

In contrast, orthogonal rotation produces factors that are uncorrelated. Orthogonal method has several options for rotation; quartimax, varimax, and equamax. (Costello and Osborne 2005) stated that orthogonal rotation produces more easily interpretable results and is slightly simpler than oblique rotation.

Varimax rotation which was developed by (Thompson 2004) is the most common form of rotational methods for exploratory factor analysis and will often provide a simple structure. On the other hand, Fabrigar et al. (1999) stated that there is no widely preferred technique of oblique rotation and all techniques tend to produce similar outputs.

4.5 Interpretation

Interpretation is the process of examination to select variables which are attributable to a construct and allocating a name for that construct. The labeling of constructs is a theoretical, subjective and inductive process (Pett, Lackey et al. 2003). It is significant that labels of constructs reflect the theoretical and conceptual intent.

For instance, a construct may includes four variables which all related to the user satisfaction thus the label “user satisfaction” will be assigned for that construct. (Henson and Roberts 2006) stated that in order to providing a meaningful interpretation, at least two or three variables must load on a factor.

5 Conclusions

Factor measurement, definition and instrument validity are vital to information system, social science, education and psychology. EFA is a complex multivariate statistical method involving many linear and sequential steps. The intention of this research was to provide the fundamental information about EFA with a stepwise and user-friendly guideline.

The paper suggest a five stem guide for implementation of exploratory factor analysis which includes: (1) evaluation of sample size adequacy using correlation matrix, Kaiser-Meyer-Olkin (KMO) and Bartlett's Test techniques, (2) choosing factor extraction method such as principal components analysis, principal axis factoring, image factoring, maximum likelihood, alpha factoring, unweighted least squares, generalised least squares and canonical, (3) selecting factor retention methods using; cumulative percentage of variance, K1 - Kaiser’s , scree Test, minimum average partial approaches and parallel analysis, (4) selection of rotational method, whether orthogonal rotations or Oblique rotation and finally, (5) interpretation and labeling of factors.

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