The Asian Journal of Shipping and Logistics 34(2) (2018) 091-111

Contents lists available at ScienceDirect

The Asian Journal of Shipping and Logistics

Journal homepage: www.elsevier.com/locate/ajsl

Use of Exploratory Factor Analysis in Maritime Research

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A R T I C L E I N F O

Article history:
Received 15 September 2017
Received in revised form 15 February 2018
Accepted 31 May 2018

Keywords:
Exploratory factor analysis
EFA
Factor loading
Maritime
Information sharing
Supply chain

A B S T R A C T

The purpose of this paper is to discuss the approaches that are undertaken while applying exploratory factor analysis (EFA) in maritime journals to attain a factor solution that fulfils the criteria of EFA, achieves the research objectives and makes interpretation easy. To achieve the aim of this paper, published articles across maritime journals will be examined to discuss the use of EFA. This will be followed by an example of EFA using an empirical data set to emphasise the approaches that can be undertaken to make appropriate decisions as to whether to retain or drop an item from the analysis to attain an interpretable factor solution.

The results of this study demonstrate that majority of maritime studies employing EFA retain a factor solution based on the researchers' subjective judgement. However, the researchers do not provide sufficient information to allow readers to evaluate the analysis. The majority of the reviewed papers failed to provide important information related to EFA explaining how the final factor structure has been acquired. Furthermore, some papers have failed to justify their decisions, for example, for deleting an item or retaining factors with single measured variable.

The first contribution of this study is the analysis of how studies carried out in the maritime sector have been applying EFA in their studies. The second contribution of this study is to provide future researchers aiming to use EFA in their studies for the first time an example of a complete EFA process, explaining different steps that can be undertaken while carrying out EFA.

1. Introduction

Factor analysis is often used in research to explain a large number of measured variables (survey items) with a small number of underlying factors (latent variables) (Henson and Roberts, 2006). These latent variables can be used in following analyses such as regression or cluster analysis. In addition, factor analysis is also used to assess the validity of the measures (extent to which the constructs represent the original

http://dx.doi.org/10.1016/j.ajsl.2018.06.006

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Peer review under responsibility of the Korean Association of Shipping and Logistics, Inc.

variables) (Cortina, 1993, Henson and Roberts, 2006, Tabachnick and Fidell, 2007). The application of EFA in maritime research is extensive because majority of the factors involved are not quantifiable and hence are measured through several indicators. Factors such as, those that enhance the service quality in ports, selection criteria in container shipping, those that evaluate the expectations of cruise travellers and those that strengthen the competitive position of exporters are some examples of the types of factors that come across in maritime sector which need to be measured through observed variables (Cerit, 2000, Pantouvakis, 2006, Chang et al., 2016). Moreover, the number of articles using latent variables are increasing which means there are more articles with indicator variables and hence there has been an increasing use of EFA in maritime studies. EFA helps in reducing large number of indicator variables into limited set of factors based on correlations between variables.

Because EFA involves inherent subjectivity (researcher judgement for interpretability), it has been criticised by many authors (Tabachnick and Fidell, 1996). According to Tabachnick and Fidell (1996), EFA results in an infinite number of mathematically identical solution which are difficult to be differentiated through objective criteria. EFA requires several decisions, which might vary depending on the researcher or the research, to be made in each individual stage resulting in different solutions under different conditions (Kieffer, 1999). While articles in maritime sector that have employed EFA have also made their decisions subjectively, such decisions have not been adequately justified. In addition, there has been an absence of detailed explanation on how and why a particular output is retained as the final factor structure. Furthermore, there are some common problems experienced in shipping-specific EFA studies such as measuring factors with single variables (Lu and Marlow, 1999, Cerit, 2000, Lai et al., 2004, Pantouvakis, 2006, Paixão Casaca and Marlow, 2009), retaining a factor with low/very low Cronbach alpha value (Cerit, 2000, Jenssen and Randøy, 2006), deletion of variables without any justification (Esmer et al., 2016), inappropriate calculation of factor scores (Jenssen and Randøy, 2002, Lu and Marlow, 1999, Pantouvakis, 2006, Wen and Lin, 2016) and lack of justification for the selection or deletion of cross-loaded items (Lu et al., 2016c, Bandara et al., 2016).

Several studies provide details about methodological decision criteria involved in exploratory factor analysis, such as checking the appropriateness of the data for EFA (KMO and Bartlett's test of sphericity), rotation (e.g.: Varimax or Promax), factor extraction/retention criterion, cut-off value for acceptable factor loadings and the suitable percent variance explained (Henson and Roberts, 2006, Fabrigar et al., 1999, Osborne and Costello, 2009). There are a number of circumstances that a researcher might come across where she/he has to make subjective decisions considering a number of traits such as the loadings, cross-loadings, number of items under each factor and factor scores. For researchers, applying EFA for the first time, this might be a difficult decision to make. Limited studies have provided detailed explanation of how a researcher makes decision to select the factor structure that is acceptable and interpretable. Furthermore, studies that employ EFA do not explicitly inform readers about the strategies used in making decisions to achieve satisfactory factor solution. Often, because of word limit and applied nature, the explanation is concise. Since the decisions might vary according to the research or the researcher, an example might better explain readers as to what and how decisions can be made.

The aim of this paper is to provide future researcher aiming to use EFA in their studies an idea as to how an acceptable, justifiable and interpretable factor solution can be obtained. The paper will first discuss some major methodological decisions that researchers must make when conducting EFA. This will be followed by a review of the papers published in maritime journals to discuss the use of factor analysis in the maritime domain. The review process will especially point out how low factor loadings and cross-loadings have been dealt with and the criterion used for item exclusion. An example of EFA using an empirical dataset from Nepal will then be presented in detail providing the readers with necessary information about why a particular decision was taken. It will then report the final output which the researcher deems as satisfactory and then will explain how factor scores can be calculated and be used in subsequent analysis. The final section provides recommendations for future practice and draws conclusions.

2. Methodological Decisions for Conducting an EFA

This study assumes that readers know the basic concept of EFA and hence, provides a brief review of the methodological decisions that need to be taken for conducting an EFA. For further details on methodological decisions (such as KMO and Bartlett's test of sphericity, factor extraction method, factor retention rule, factor rotation and percentage of variance explained), refer to Tinsley and Tinsley (1987), Comrey and Lee (1992), Tabachnick and Fidell (1996), Fabrigar et al. (1999), Henson and Roberts (2006) and Osborne and Costello (2009). It is important for researchers to inform readers about the methodological decisions made while conducting EFA. Based on research objectives, these methodological decisions can result in different outcomes. The methodological decisions discussed are related to the methods of factor extraction, factor retention rule and factor rotation (Tinsley and Tinsley, 1987, Fabrigar et al., 1999, Henson and Roberts, 2006).

2.1. *Factor Extraction*

Statistical software packages such as IBM SPSS offers seven factor extraction methods out of which principal component analysis (PCA) is the most widely used. PCA is appropriate when the goal is to reduce a large number of measured variables into a small set of composite variables representing them (data reduction) (Fabrigar et al., 1999). While PCA is considered as a method of factor analysis, it is not factor analysis at all because it does not fulfil the goal of EFA, i.e. to arrive at a parsimonious representation of the associations among measured variables (Fabrigar et al., 1999). However, the results produced by factor analysis and PCA are quite similar and is often negligible in terms of interpretation (Fabrigar et al., 1999, Osborne and Costello, 2009). Please refer to Fabrigar et al. (1999) for detailed explanation on PCA and factor analysis.

Besides PCA, principal axis factoring (PAF) is also used when the focus is on the common variance (association) among the observed variables (Fabrigar et al., 1999, Henson and Roberts, 2006). Other than PCA and PAF, maximum likelihood (ML) is another popular factor extraction method. Depending on the research aim, one can decide to select any factor extraction method. In the example provided in this paper, the aim was to reduce a large number of measured variables (58 items) into a small set of composite variables (16 components) and hence, PCA was applied.

2.2. *Factor Retention*

The next decision to follow factor extraction is to decide the number of factors to retain. While in factor analysis, the total number of factors equals the number of variables entered, it is not necessary to retain all the factors as they do not contribute much to the overall solution (Henson and Roberts, 2006). Different factor retention techniques have been suggested to retain the right number of factors. There are problems associated with over-factoring as well as under-factoring (Tinsley and Tinsley, 1987, Fabrigar et al., 1999). While over-factoring will cause all the major factors to be accurately represented, there might be some additional factors with single measured variable that load on them. In case of under-factoring, measured variables that were supposed or meant to load on factors that are not included in the model can falsely load on factors that are included in the model, resulting in poor estimates of the factor loadings. Hence, it is important to determine an optimal number of factors.

The criteria to retain all the factors with Eigen values greater than 1(Kaiser Criterion) is the default in most statistical packages and is one of the most widely used criterion. However, this method has been controversial as it is claimed to overestimate in some cases, while underestimate in others (Fabrigar et al., 1999, Henson and Roberts, 2006, Osborne and Costello, 2009). Other available options are scree test (criticised for its subjective nature) and parallel analysis. While parallel analysis has been considered the most accurate procedure, it is rarely used in published research (Hayton et al., 2004). Researchers' main goal is to retain the number of factors which will represent the measured variables well and fulfils their research requirement. Based on the research aim, researchers can try different procedures and choose the one that fulfils the aim. In addition, it is also advisable to use multiple criteria and check if all procedures suggest the same number of factors to be retained.

2.3. *Factor Rotation*

Factor rotation is essential for easy interpretation. While rotation cannot change the basic aspects of the analysis (such as loadings or variance explained), it simplifies and clarifies the data structure (Osborne and Costello, 2009). Rotation can be conducted in two ways based on whether the focus is to produce factors that are uncorrelated (orthogonal rotation) or to produce factors that are correlated (oblique rotation). Varimax rotation has been considered as the best and most widely used orthogonal rotation although there is no single dominant method of oblique rotation (Fabrigar et al., 1999). While in real world, factors are always correlated, researchers can choose to represent the factors as uncorrelated to meet the statistical assumptions of the research problem (Hair et al., 2003). For example, multiple regression analysis requires factors to be uncorrelated (multicollinearity) and hence, choosing orthogonal rotation can be one way to ensure multicollinearity.

3. Methodology

Maritime journals/special issues associated with International Association of Maritime Economics (IAME) 2017 were reviewed to examine the use of EFA in maritime sector. *Maritime Economics and Logistics*, *Maritime Policy and Management*, *Maritime Business Review and The Asian Journal of Shipping and Logistics* were selected. Exploratory factor analysis was used as keyword to search for relevant journal articles. Articles that employed EFA were selected for review, while articles that only used CFA were discarded. The search resulted in 372 articles published from 1999 to 2016. Thirty-five papers that used EFA were identified which were reviewed to examine the decision criteria adopted by different researchers. The review involved the analysis of several aspects under EFA, such as factor extraction/retention/rotation, reasons for item exclusion, number of factors retained, percentage of variance explained, number of items deleted and the calculation of factor scores.

For the example presented in this study, a survey questionnaire was developed and data were collected from supply chain participants in Nepal. The survey questionnaire comprised of 58 items based on 21 factors identified from the literature. The sample was randomly selected from the lists of associate members of the Federation of Nepalese Chamber of Commerce & Industries (FNCCI) and Nepal Freight Forwarders Association (NEFFA). From 215 organisations invited to participate in the survey, 131 responses were received representing a response rate of 60.93%. The aim of conducting an EFA was threefold: 1) to uncover the factors underlying the data set; 2) to assess the validity (unidimensionality, convergent validity and discriminant validity) of the factors; and 3) to compute the factor scores to be used in subsequent analyses.

4. Results

As previously mentioned, EFA can result in a number of solutions based on subjective decisions made by the researcher. Because of this, it is likely that readers will have individual evaluation of the results obtained in an EFA (Tinsley and Tinsley, 1987, Henson and Roberts, 2006). However, majority of the articles using EFA do not provide sufficient information to allow readers to make independent interpretations or to understand how and why the final result was obtained. The following section discusses the information provided and the information missing in EFA reporting of the articles published in maritime journals. Table 1 exhibits different decision criteria used by different papers.

Lu and Marlow (1999) collected data from liner shipping companies, agencies and ocean freight forwarders from Taiwan. EFA was employed to summarise a large number of shipping service attributes through a small number of underlying dimensions called strategic groups. Variables with factor loadings above 0.3 were extracted. Eight factors were extracted with Factor 8 consisting of only one measured variable. This study does not discuss cross-loadings and deletion of any item. The total scores on each factor were used for cluster analysis. Cerit (2000) conducted EFA to identify factors that help strengthen the competitive position of exporters by collecting data from dried fruits exporters in Turkey. Three sets of EFA were conducted for three categories of factors in the context of international marketing. None of the items were deleted. While they considered items with factor loadings greater than 0.7 as practically significant, items with factor loadings up to 0.4 were retained. The first EFA extracted 6 factors with one factor consisting of only one measured variable. There was one item with negative loading. However, no explanation was provided for the negative loading. In addition, they have retained a factor with Cronbach's alpha of 0.22 which is very low compared to the alpha value considered to be reliable, i.e. 0.7 or above (Nunnally, 1967).

The main aim of conducting EFA for Jenssen and Randøy (2002) was to assess the validity of and to reduce the number of measured items for independent (organisational factors) and dependent constructs (innovation). The respondents were investor contacts of 63 Norwegian shipping companies. They conducted 8 EFAs for independent constructs, each for group of items which were assumed in advance to be representing different concepts. With EFA, they were able to reduce the dataset of 74 items to 19 items. The factor analysis of the dependent variable ‘innovation’ revealed four factors. In this study, factors were deleted rather than individual items. The exclusion criterion was to delete the factors that contributed less than 15% of the variance in the factor analyses. However, the result does not show the variance explained by each factor. In addition, important information is missing which makes it difficult for readers to understand what is actually being done (the measured variables, factor loadings, percent variance explained, factor retention criteria and rotation). They have not discussed how the factor scores were calculated for subsequent regression analysis.

To examine whether the underlying constructs were represented by a list of 24 logistics services (measured variables), Lai et al. (2004) conducted an EFA with Varimax rotation. Logistics service providers (LSPs) in Hong Kong were the respondents in this study. While in this study, eigenvalue criterion was used to determine an initial set of factors, the interpretability of the factors was used to determine the final set of factors. They considered 0.5 as the cut-off value to retain the items. Another exclusion criterion was to delete those items that loaded on more than one factor with loadings of 0.5 or greater. The elimination process resulted in 14 out of 24 logistics services remaining (9 items deleted simultaneously after first EFA and one item deleted after second EFA). The final EFA was conducted with 14 items which resulted in 3 factors with one factor having only one variable. Furthermore, they conducted cluster analysis using the composite scores of the extracted factors. The composite scores were calculated by taking the arithmetic means of their underlying items.

A reliability test was conducted before conducting an EFA by Pantouvakis (2006) and deleted 3 items to improve the alpha values. With data collected from passengers travelling from the three Greek ports, EFA was performed with 20 items to test the hypothesis which introduced a four-dimensional construct for port service quality. Items with loadings below 0.4 were supressed (selected an option in SPSS or another statistical package). Further analysis (cluster analysis) was conducted using the factor scores. However, Pantouvakis (2006) has not explained how the factors scores were calculated. Cheng and Choy (2007) used EFA in their study to summarise the identified items into a new and smaller set of success factors of quality management in the shipping industry. The data for this were collected from the ship-owner members of BIMCO and INTERTANKO. Before conducting EFA, they deleted nine items based on corrected item-total correlation and Cronbach’s alpha value. In EFA, the exclusion criteria were to delete 1) items with factors loadings below 0.5; and 2) items that cross-loaded on multiple factors with loadings greater than 0.4. The elimination criteria resulted in the elimination of 14 measurement indicators. In total, Cheng and Choy (2007) deleted 23 items in their study. Pantouvakis et al. (2008) collected data from passengers of Piraeus Passenger Port in Greece and used EFA to explain the pattern of relationships within the data set and to compare them against the hypothesised SERVQUAL dimensions. With the criterion to suppress items with loadings lower than 0.40, one (item 20) out of 22 items failed to load on any factor. However, the article does not discuss further about it. Furthermore, it is mentioned that item 4, 10 and 15 were excluded from subsequent analysis due to one reason being multi-factor loadings from EFA. However, the cross-loadings were not discussed further.

Norzaidi et al. (2009) used EFA to assess construct validity of the factors that affect the port middle managers’ job performance. The respondents were from private (terminal operators) and public (the marine department, royal customs and excise department, the immigration department and port authority) sectors. The item deletion criteria were to delete items with similar loadings on two factors and with loadings less than 0.5. In this study, reliability test was performed before conducting EFA and six EFAs were conducted for six constructs used in this study. Lu et al. (2010) conducted EFA to identify and summarise a large number of container development strategic attributes into a smaller, manageable set of underlying factors. The data were collected from shipping academics, employees of port authorities and container shipping managers and executives. The authors extracted only items with loadings > 0.5 and deleted all the items with cross-loadings. Lirn et al. (2014) conducted EFA followed by CFA to identify three critical green shipping management capability dimensions by collecting data from container shipping firms in Taiwan. In this study, variables with loadings of 0.5 or greater on only one factor were extracted. This extraction criterion means that 1) loadings ≥ 0.5 will be retained; and 2) if an item loads on two factors with one loading ≥ 0.5 and the other loading < 0.5 (even though the loading is 0.4), item with loading ≥ 0.5 will only be extracted. In other words, in case of cross-loadings, the loading on the factor with factor loading < 0.5 will be ignored. Following this criterion, none of the items were deleted. Hence, this criterion resulted in fewer number of item deletion. For example, Item G19, G23, G31, G34 and G0 were retained even though they loaded on two factors with loadings above 0.4.

Pantouvakis and Psomas (2016) conducted EFA to extract five total quality management (TQM) practises and four TQM results latent factors in shipping companies. The respondents of this study were the senior managers of Greek shipping companies. In this study, the exclusion criteria were to delete all the items with factor loadings below 0.6 and multi-factor loading (cross-loading) variables. However, the EFA results tables shows that there were five items with loadings < 0.6 (> 0.55). Furthermore, they used the summated scales of all the respective measured items for each independent and dependent variable to conduct multiple regression analyses. Yuen and Thai (2016) performed EFA to identify a smaller number of factors to represent the list of barriers of supply chain integration (SCI) in maritime logistics industry. Data for this study were collected from 90 container shipping firms located in Singapore. A minimum difference of 0.50 between the first and the second largest factor loading on a single measure defined the absence of cross-loading. There were no cross-loadings on any measure and hence, the exclusion criterion was to delete all the items with factor loadings below 0.6.

EFA was used by Lu et al. (2016c) to summarise a large number of sustainability assessment criteria in the context of international port sector into a small number of underlying dimensions. The managers and supervisors at major international ports in Taiwan were the respondents in this study. The authors retained only the items with loadings greater than 0.5. In this study, only one item was deleted as it loaded on two factors with loadings less than 0.5. It is not clear whether they selected the option to supress all the loadings below 0.5 before running the EFA or they deleted the items with loadings below 0.5 after running the EFA. If they selected the first option, the EFA result would not have displayed the cross-loaded items because both loadings are below 0.5. However, it is not advisable to supress values under a threshold value of 0.4 because loadings above 0.4 are considered important and need to be discussed. Furthermore, the EFA output table shows that (considering cross-loadings greater than 0.4) “decreasing noise pollution” loaded on factor 1 (loading = 0.566) and factor 2 (loading = 0.407). Similarly, “decreasing greenhouse gas emission” loaded on factor 1 (loading = 0.444) and factor 3 (loading = 0.653). However, they failed to explain why they selected the items with higher loadings and ignored the cross-loadings.

Table 1 Exploratory Factor Analysis Decision Criteria

Reference	Factor Extraction	Factor Retention	Rotation	KMO	Sample Size	Number of Items	Reason for Excluding an Items	Factors Retained & Variance	Number of Items Deleted	Reliability/ Validity Value	Factor Score Calculated? How?	CFA Employed?
Lu and Marlow (1999)	PCA	EV > 1 & scree test	Varimax	x	72	39	Loadings < 0.3	8 factors → 70%	6 (test before EFA)	α > 0.7	Yes Summated scores	No
Cerit (2000)	PCA	x	Varimax	x	61	55	Loadings < 0.4	6 factors →73.8% 5 factors →74.1% 2 factors →73.6%	0	α > 0.2	No	No
Jenssen and Randøy (2002)	PCA	x	Missing	x	63	74 (Inde) Not clear	Factors that contributed < 15% of the variance	8 independent and 3 dependent	55 out of 74 Not clear	α > 0.57	Yes x	No
Lai et al. (2004)	PCA	EV > 1	Varimax	x	221	24	Loadings < 0.5 and cross-loadings = > 0.5	3 factors →68.8%	10 out of 24	α > 0.7	Yes Mean score	No
Pantouvakis (2006)	PCA	x	Varimax	0.84	403	23	Loadings < 0.4	6 factors → 63%	3 (reliability test) 2 out of 20	α > 0.7	Yes x	No
Jenssen and Randøy (2006)	PCA	x	Missing	x	46	Not clear	Not clear	Not clear	Not clear	α > 0.5	No	No
Cheng and Choy (2007)	PCA	EV > 1	Varimax	> 0.50	161	39	Loadings < 0.5 and cross-loadings	4 factors →72.2%	9 (tests before EFA) 14 out of 30	α > 0.7	No	No
Pantouvakis (2007)	PCA	x	Varimax	0.75	213	14	Not clear	3 factors →56.8%	0	α > 0.8	No (calculated from another set of data)	No
Pantouvakis et al. (2008)	PCA	x	Promax	0.97	434	22	Cross loadings	2 factors →69.5%	3 out of 22	α > 0.8; AVE > 0.5	No	Yes
Paixão Casaca and Marlow (2009)	PCA	EV > 1 & scree test	Missing	x	72	75	Not clear	13 factors →74.5%	3 (test before EFA) 0 out of 72	α > 0.7	No	No
Norzaidi et al. (2009)	PCA	EV > 1	Varimax	> 0.60	36	26	loadings < 0.5 and similar loadings on two factors	Not mentioned	Not mentioned	α > 0.7; $\boldsymbol{X}$2/DF=0.985 ; CFI, IFI, TLI> 0.9; RMSEA=0.02	No	Yes
Triantafylli and Ballas (2010)	PFA	EV > 1 & scree test	Promax	x	75	Not clear	Not clear	2 factors → 55.8%	Not mentioned	x	Yes x	No
Oltedal and Wadsworth (2010)	PCA	EV > 1	Varimax	0.89	1262	31	Loadings < 0.5	8 factors → 67.1%	Not mentioned	α > 0.7; item-total corr. > 0.4; 0.3< inter-item corr.< 0.8	Yes x	No
Lu et al. (2010)	PCA	x	Varimax	x	175	19	Loadings < 0.5 and cross-loadings	3 factors → 62.7%	5 out of 19	α > 0.69	x	No
Bae (2012)	x	EV > 1	Not clear	x	182	47	Loadings < 0.5	7 factors → 80.9% 3 factors → 75.5%	8 out of 47	α > 0.8; GFI, CFI, NFI & IFI>0.9; AGFI>0.8; RMSEA < 0.08	s	Yes
Cheng and Choy (2013)	PCA	EV > 1	Varimax	> 0.50	161	28	Loadings < 0.5 and cross-loadings	3 factors → 73.1%	6 (tests before EFA) 13 out of 22	α > 0.8	Yes x	No
Lirn et al. (2014)	x	EV > 1	Varimax	x	80	16 10	Loadings < 0.5 and cross-loadings	3 factors → 73.6% 2 factors → 85.8%	0 out of 16 1 out of 10	α > 0.8; CFI, TLI > 0.9 RMSEA = 0.08	No	Yes
Dahl et al. (2014)	PCA	EV > 1	Varimax	0.819	754	18 5	Loadings < 0.4 and cross-loadings	6 factors → 65% 1 factor → 45.7%	0 out of 18 0 out of 5	α > 0.6	Yes x	Yes
Thai et al. (2014)	PCA	EV > 1	Varimax	0.78	74	27	Loadings < 0.5 and cross-loadings = > 0.5	5 factors → 70.1%	8 out of 27 1 after reliability	α > 0.7	No	No
Tsai (2014)	PCA	EV > 1	Not clear	0.948	382	Not clear	Loadings < 0.5	4 factors → 69.3%	Not clear	α > 0.7	Yes x	No

Bae and Ha (2014)	x	EV > 1	Missing	> 0.8	219	51	Loadings < 0.6 and cross-loadings	1 factor → 79.3 3 factors → 75.5% 3 factors → 70.5% 3 factors → 76.8%	14 out of 51	α > 0.8	x	No
Bhattacharya (2015)	PCA	EV > 0.9	Varimax	0.91	433	18	Loadings < 0.5	6 factors → 63.1%	1 (test before EFA) 0 out of 17	α > 0.7	x	No
Sadovaya and Thai (2015)	PCA	x	Varimax	0.88 0.76	Not clear	53 32	Loadings < 0.5 and cross-loadings = > 0.5	6 factors → 72.4% 6 factors → 71.2%	22 out of 53 8 out of 32	α > 0.6; CMIN/DF<3; CFI>0.9; RMSEA<0.05 : RMR<0.05	No	Yes
Pantouvakis and Psomas (2016)	PCA	x	Varimax	> 0.8	87	Not clear	Loadings < 0.5 and cross-loadings	5 factors 4 factors	Not mentioned	Loadings>0.6 ; AVE>0.5;	Yes Summated score	No
Yuen and Thai (2016)	ML	EV > 1	Promax	0.896	90	21	Loadings < 0.6	5 factors → 72.3%	0 out of 21	α > 0.8	No	No
Lu et al. (2016c)	x	EV > 1	Varimax	0.92	135	31	Loadings < 0.5 and cross-loadings	4 factors → 64.2%	1 out of 31	α > 0.85; CMIN/DF<2; GFI, AGFI, TLI, NFI>0.9; RMSEA<0.08 ; RMR=0	No	Yes
Lu et al. (2016b)	x	EV > 1	Varimax	x	135	33 16 9	Loadings < 0.5 and cross-loadings	2 factors → 80.4% 2 factors → 74.6%	0 out of 33 0 out of 16 0 out of 9	α > 0.8; CMIN/DF<2; GFI, TLI, NFI>0.9; RMSEA<0.08 ; RMR=0	No	Yes
Lu et al. (2016a)	x	EV > 1	Varimax	x	141	19 12 14	Loadings < 0.5 and cross-loadings	3 factors → 69.2% 3 factors → 84.9% 2 factors → 63.6%	1 out of 19 0 out of 12 0 out of 14	α > 0.8; CMIN/DF<2; CFI, TLI>0.9; RMR<0.05	No	Yes
Yang (2016)	PCA	EV > 1	Varimax	x	184	15	Loadings < 0.5	5 factors → x	0 out of 15	α > 0.7; CMIN/DF<2; GFI, CFI, IFI>0.9; RMSEA<0.08 ; RMR=0	No	Yes
Fenstad et al. (2016)	PFA	EV > 1	Varimax	0.81	244	18	Loadings < 0.4 and cross-loadings = > 0.4	6 factors → 63.4%	0 out of 18	α > 0.7	No	Yes Confirm EFA
Chang et al. (2016)	x	x	Missing	x	97	21	Cross-loadings	3 factors → x	1 out of 21	α > 0.9; NC < 3; SRMR < 0.05; CFI < 0.9	Yes Mean score	Yes
Bandara et al. (2016)	PCA	EV > 1	Varimax	0.67	67	28	Loadings < 0.6	5 factors → 72.5%	10 out of 28	α > 0.7; CMIN/DF< 2; PCLOSE = 0.526	No	Yes
Wen and Lin (2016)	PCA	EV > 1	Varimax	0.9	156	23	Loadings < 0.4	4 factors → 68.8%	0 out of 23	α > 0.7	Yes x	No
Kim et al. (2016)	PCA	EV > 1	Varimax	0.86	203	21	Loadings < 0.5	4 factors → 64.5%	2 out of 21	α > 0.7	x	No
Esmer et al. (2016)	PCA	EV > 1	Varimax	x	42	26	Not clear	5 factors → 80%	13 out of 26	CMIN/DF = 1.71; PCLOSE < 5%	No	Yes

Chang et al. (2016) performed EFA to develop a measurement scale for evaluating the expectations of cruise travellers during their visit to a port of call in Asia using 21 measurement items. The data for this study were collected from the travellers on-board the Coasta Atlantica and the Mariner of the Seas. One item was deleted due to cross-loading problem. In this study, EFA has been explained very briefly. Factor scores were calculated by averaging the item scores that comprised the corresponding factor for regression analysis that followed. EFA was carried out by Bandara et al. (2016), with data collected from port authorities managing world container ports, to identify the factors influential to the selection of the infrastructure tariff design model. They considered only those items with loadings above 0.6 as the significant items underlying a construct. While it has not been discussed why and how many items have been deleted, the comparison of Tables 2 and 3 shows a discrepancy of 10 items. Furthermore, they failed to discuss items that loaded on more than one factor. The EFA result table exhibits three items (use of cost-based pricing, attracting specific cargo and port users and port infrastructure cost) loading on two factors with factor loadings above 0.5 which have not been discussed by Bandara et al. (2016).

EFA was conducted by Wen and Lin (2016) to summarise 23 ocean carrier service attributes by a small number of latent factors with data collected from international freight forwarders that provide services between Taiwan and Southern China. Following EFA, any Item with factor loadings greater than 0.45 were retained in the final result. In this study, none of the items were deleted and it is unclear whether there were any items with cross-loadings. They mentioned that the result of factor analysis provides factor scores for subsequent cluster analysis. However, it is ambiguous whether the factor scores were calculated as part of the EFA or as a summated score based on EFA output. Esmer et al. (2016) conducted EFA to identify the underlying strategies (factors) in non-price competition in the port sector by collecting data from Turkish ports. While the authors do not explain the number of items deleted and the reason for deletion, the EFA output table shows that out of 26 items, 13 were deleted. Of the remaining 13 items, all have factor loadings over 0.7 and there are no cross-loadings > 0.4.

5. Discussions

The review of the 35 articles published from 1999 to 2016 shows that different authors have selected different criteria to decide the final factor structure. While it is a powerful tool, considerable attention should be paid while interpreting the results. For the methodological decisions, majority (> 50%) of the articles selected principal component analysis, factors with Eigenvalue > 1 (Kaiser Criterion) and Varimax rotation as the factor extraction, retention and rotation criteria. This result is in line with the studies conducted by Ford et al. (1986) and Peterson (2000). From the same data, changing one or all three decisions can result in different patterns. Furthermore, majority of the papers employed Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to assess the suitability of the sample for PCA. While almost 43% of the reviewed papers did not report the KMO value, the remaining 57% papers reported KMO values greater than 0.5 which is acceptable (Hair et al., 1998).

Low factor loadings and cross-loadings are the main reasons used by many authors to exclude an item. However, the cut-off value for factor loading were different (0.5 was used frequently). There is no consensus as to what constitutes a “high” or “low” factor loading (Peterson, 2000). As too much subjectivity has been used to guide interpretation, it is important to establish some rules that should be followed to aid interpretation (Ford et al., 1986). While loadings above 0.4 are used commonly to consider a variable as significant (Comrey and Lee, 1992), high factor loading suggest that the measured variable is a good representation of the factor. Items, loading strongly on only one factor, will also confirm unidimensionality and validity of the measures (Cortina, 1993, Ahire and Devaraj, 2001). Hence, it is advisable to consider items with loadings of 0.5 and above in defining a factor as they are considered practically significant. While all the papers extracted less than ten factors, one paper extracted 13 factors. Furthermore, different criterion was used to deal with cross-loadings. Researchers selected 0.4 or 0.5 as a cut-off value to consider an item to have multiple-loadings as every item load on each factor. While some researcher decided to drop the items with cross-loadings, other researchers considered the item to be an indicator of the factor on which it loaded with higher loading. Several cross-loading items in a data set signify that the items were poorly developed. Hence, careful attention should be paid while designing the survey items.

Majority of the papers used the phrase ‘variables with factor loadings greater than ____ (cut-off value) were extracted.’ It was not clear whether 1) they selected the option provided by statistical packages to supress small factor loadings; or 2) they deleted the items with loadings below the cut-off value. Selecting the first option makes it easier because if you ask SPSS to supress all the loadings below 0.5, only the items with loadings 0.5 and above will be displayed. Hence, a researcher will not have to deal with cross-loadings below 0.5. While researchers tend to supress loadings under 0.4, it is not a good practice to supress loadings above this value. Loadings above 0.4 should be noted and then explained if the researcher decides to drop it. Some papers have not provided the actual items used in the factor analysis and the resulting factor loading matrix without which it is difficult for the readers to understand the authors’ interpretation as well as provide their own interpretation of the research findings.

Almost all papers have chosen internal consistency as a method to assess reliability by calculating Cronbach’s alpha value. While most papers reported alpha values well over 0.7, some studies had alpha value less than 0.7 with one paper accepting alpha value as low as 0.2. Furthermore, 40% of the reviewed papers have conducted CFA in addition to EFA to assess the validity of the data. In social sciences, a solution that accounts for more than 60 percent of the variance is considered acceptable (Zikmund et al., 2010). While some papers did not mention the percentage of variance explained by the factor structure, in majority of the papers, the selected factor structure explained more than 60% of the variance. Moreover, few papers discussed the total number of items deleted to obtain a clear and interpretable factor solution.

One important aspect that needs to be discussed is the sample size requirement for conducting EFA. There have been no unanimous recommendations/guidelines regarding the sample size requirement for EFA, such as minimum necessary sample size N or minimum ratio of N to the number of variables being analysed p (MacCallum et al., 1999). The nature of the data play an important role in determining the suitability of the sample size (Fabrigar et al., 1999, MacCallum et al., 1999). According to Costello and Osborne (2005), data with uniformly high communalities without cross-loadings and several variables loading strongly on each factor is considered as strong data. However, large sample is preferable to produce generalisable results. The sample size and the number of items in the reviewed papers range from 36 – 1262 and 5 – 75 respectively. With a sample size of only 36, Norzaidi et al. (2009) carried out EFA on 26 items. Another noticeable case is in Paixão Casaca and Marlow (2009) where an EFA was employed on 75 items with data collected from 75 respondents only. However, majority of the reviewed papers have not discussed sample size in detail.

Finally, only three papers have explained how the factor scores were calculated for subsequent analysis out of which none calculated the factor score from EFA (option provided in SPSS while running EFA). Out of three papers, one stated that the factor scores were calculated by summing up the variables while the other two used the mean value as factor score. According to Ford et al. (1986), these procedures yield composite scores rather than factor scores and is inappropriate to refer them as factor scores. The main drawback of using the mean or the sum scores is that all items on a factor are given equal weight regardless of their loadings. This will result in less reliable factor score because it ignores the amount of variability in the observed variable caused by the factor (DiStefano et al., 2009). For the remaining papers that calculated the factor scores, it was difficult to determine how they were calculated.

Majority of the reviewed papers have not explained how the items were deleted, either simultaneously or one at a time. Removing a single item from the data set tend to result in a different outcome which is why it is necessary for a researcher to distinguish the best way of dropping the problematic items. Amongst the reviewed articles, Lai et al. (2004) have provided more information than any other article. They have explained 1) why some items were deleted (low loadings and cross-loadings); 2) how many items were deleted; 3) how many times they conducted the EFA; and 4) how the factor scores were calculated for subsequent analysis (cluster analysis in their study).

6. An Example on EFA: Antecedents of Information Sharing in Supply Chains

EFA has been considered as one of the best tool to test the relationship between the observed variables and their underlying constructs (latent variable) (Byrne, 2010). Item loadings under only one factor will confirm unidimensionality and discriminant validity (Cortina, 1993, Ahire and Devaraj, 2001). In addition, all the items loading substantially (factor loadings above 0.5) on their underlying constructs will confirm convergent validity (Ahire and Devaraj, 2001, Tabachnick and Fidell, 2007, Du et al., 2012). EFA can also be used to compute the factor scores to be used in subsequent analyses (e.g. regression analysis) and is considered more reliable than the summed score or mean score technique.

In the following example, exploratory factory factor analysis was carried out in IBM SPSS 21 to identify the antecedents of information sharing in supply chains. The final factor structure extracted 16 factors as the influential factors of information sharing in supply chains. This paper will explain step by step how the final factor structure was attained and criteria used to fulfil the requirements of EFA. The final factor structure is presented in Table 2 and the remaining 8 EFA outputs are presented in **Appendix 2**. The measurement variables along with their factor loadings and variance explained are presented in **Appendix 1**.

Table 2 Exploratory Factor Analysis (Final)

	Component															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Item 47	.803	-.023	.100	-.009	.115	.112	.227	.042	.034	.026	.002	-.033	.037	.188	-.018	.180
Item 46	.801	-.043	.212	.047	.068	.013	.035	.119	-.060	.008	-.022	-.007	-.020	.156	-.061	-.016
Item 48	.765	.022	-.155	.188	.020	-.024	.031	.182	.147	.213	.015	.003	-.047	.033	-.010	.168
Item 50	.655	.039	.318	.087	.054	-.004	.186	.078	.036	-.072	.143	-.014	.146	-.042	.107	-.042
Item 49	.579	.027	.397	.117	.080	.087	-.005	-.042	.020	-.064	.160	.116	.150	.065	.198	.067
Item 57	.006	.921	-.062	.014	.001	.040	.118	-.024	.149	.102	.043	.098	.012	-.012	.007	.045
Item 56	.038	.912	-.038	.038	.083	.103	-.025	-.048	.135	.106	.039	.114	.041	.023	-.015	.010
Item 58	-.046	.844	.059	-.022	.106	.000	-.055	.072	-.059	.065	.130	-.035	.081	.120	.032	.088
Item 14	.183	.091	.703	.217	.045	-.002	.050	.088	.042	.034	.170	.092	.244	.001	-.046	.076
Item 13	.167	.006	.703	.308	.158	-.151	-.009	.030	-.079	-.033	.012	.098	.038	.000	.207	.184
Item 38	.157	-.032	.688	.082	.012	.143	.228	.129	.018	.000	.040	-.079	.091	-.082	-.058	-.153
Item 12	.118	-.197	.661	.020	.172	.151	-.048	.159	.144	.190	-.053	.045	-.084	.299	.003	.201
Item 35	.124	.013	.202	.850	.099	.031	.046	.110	-.040	-.011	.085	.017	.004	.078	.060	.025
Item 36	.005	-.083	.216	.844	.075	.111	-.018	.057	.041	.097	.026	.005	.124	-.023	.001	-.024
Item 34	.164	.101	.025	.826	.093	.092	.112	.055	.016	.119	-.004	-.118	.013	-.006	.137	.094
Item 53	.064	.069	.079	.041	.905	.032	.042	.034	.040	.002	-.006	.126	.026	.006	.022	.086
Item 54	.100	.150	.035	.082	.884	-.034	.024	-.010	.054	.092	.133	.040	-.069	-.057	.013	.054
Item 55	.084	-.034	.156	.173	.738	.026	-.008	.041	.042	.109	.232	.029	.126	.022	.082	.141
Item 28	.041	.057	.065	.009	.010	.852	.124	.109	.122	.174	-.016	.095	.027	.025	.107	.071
Item 30	.000	.037	.071	.095	.018	.835	.237	.055	.242	-.072	.079	-.099	.014	.011	-.050	-.018
Item 29	.115	.077	-.019	.197	-.003	.716	.228	-.135	.055	.155	.135	.223	.071	.043	.027	.179
Item 24	.027	.082	.063	.028	-.035	.182	.777	-.014	.118	.136	.060	-.052	-.033	.063	.221	.022
Item 23	.145	-.027	.006	.091	-.013	.167	.747	.078	.213	.193	.068	-.002	-.090	.042	.143	.046
Item 22	.240	-.011	.156	.020	.108	.203	.695	.019	-.011	.019	.061	-.042	.139	-.129	.048	-.010
Item 5	.044	.033	.077	.057	-.059	.049	-.039	.861	-.012	.035	-.039	-.133	.152	-.013	.184	-.049
Item 4	.181	-.009	.105	.026	.107	.129	-.033	.816	-.054	-.096	.070	-.066	.090	.078	.074	-.001
Item 6	.112	-.032	.116	.175	.005	-.136	.170	.701	-.068	.097	-.097	.196	.081	.117	-.025	.046
Item 10	.086	-.003	.016	-.077	.057	.024	.197	.004	.824	-.031	.070	.003	.159	.119	.024	-.092
Item 11	-.120	.175	.067	.011	-.015	.212	.130	-.036	.759	.068	-.052	-.039	-.030	.122	.092	.039
Item 9	.189	.098	-.003	.109	.128	.210	-.036	-.135	.685	-.098	-.015	.121	.032	.205	.107	.079
Item 26	-.035	.102	.051	.254	.055	-.040	.159	.025	.047	.802	.063	.087	.113	.010	.034	-.044
Item 27	.035	.100	-.003	-.023	-.025	.155	.142	.054	.054	.783	.058	-.027	.099	.131	-.021	.146
Item 25	.127	.126	.061	.002	.260	.129	.011	-.086	-.216	.705	-.029	-.044	-.067	.195	.028	-.170
Item 31	.082	.025	.002	-.005	.145	.122	.022	-.034	.046	.049	.826	.125	.123	-.050	.024	.053
Item 32	.014	.076	-.013	.112	.071	.007	.207	-.075	.043	.062	.810	-.087	-.010	.006	.119	.085
Item 33	.043	.099	.150	.002	.070	.008	-.043	.056	-.069	-.015	.682	-.041	-.100	.048	-.125	.009
Item 41	.080	.063	.053	-.081	.088	.063	-.088	-.077	.064	.059	.047	.870	-.039	-.024	.045	.006
Item 42	.061	.139	.091	.021	.142	.218	.025	-.049	-.068	-.002	-.041	.754	.275	.028	.055	-.031
Item 40	-.174	-.006	-.041	-.013	-.018	-.123	-.029	.109	.047	-.053	-.029	.713	-.020	.047	-.205	.296
Item 20	-.077	.041	.040	.038	-.206	.045	-.069	.118	.171	.115	-.009	.080	.735	-.144	.164	.001
Item 1	.087	.027	.023	-.001	.139	.011	.123	.303	.069	.045	.179	.102	.698	.073	-.141	.060
Item 21	.222	.100	.286	.125	.111	.134	-.094	.066	.017	.102	-.091	-.019	.656	-.025	.056	.031
Item 52	.047	-.011	-.064	-.062	-.130	.267	-.163	.134	.256	.211	.223	-.034	-.519	-.265	.258	-.100
Item 19	.140	.064	.018	.023	-.024	.007	.015	.098	.170	.150	.008	.053	-.012	.855	.102	-.036
Item 18	.164	.084	.045	.008	-.033	.058	-.033	.066	.211	.125	.010	-.016	-.008	.851	.164	-.028
Item 16	.030	.087	.146	.119	-.039	.010	.090	.116	-.034	-.023	.096	.018	-.009	.249	.791	.084
Item 15	-.029	-.018	-.014	.028	.073	.100	.182	.127	.197	.048	-.092	-.040	.031	-.047	.762	.047
Item 17	.160	-.092	-.109	.124	.178	-.071	.334	-.024	.076	.002	-.005	-.076	-.020	.315	.534	.105
Item 45	.084	.037	.118	.065	.134	.049	-.022	-.021	-.030	.080	.095	.093	.056	-.009	.038	.852
Item 44	.168	.110	.022	.023	.116	.119	.085	.006	.027	-.097	.050	.077	.037	-.038	.134	.837

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Based on the literature, 21 factors were initially identified as the influential factors of information sharing in supply chains. The survey questionnaire comprised of 58 items based on 21 factors. The 58 items were entered for Principle Component Analysis, with Varimax rotation (Hair et al., 2003). The Kaiser-Meyer Olkin measure of sampling adequacy (KMO) (> 0.50) (Hair et al., 1998) and Bartlett's test of sphericity (significant at $p < 0.001$) (Field, 2013) were used to assess the suitability of the sample for principle component analysis. Eigenvalue (>1) criterion was used to determine an initial set of factors (Hair et al., 2003). However, the interpretability of the factors was also considered to determine the final set of factors. The decision was to supress factor loadings below 0.4 (selecting an option in SPSS to supress small coefficients which will display loadings above 0.4 in the factor structure). This also signifies that cross-loadings will be considered when one loading is at least 0.4.

The initial factor structure extracted 17 factors. However, there were some items with loadings below the cut-off value of 0.5 (Comrey and Lee, 1992, Tabachnick and Fidell, 2007, Field, 2013) and some items with cross-loadings (some items loaded positively on two factors, some items loaded positively on one factor and negatively on the other). It was necessary to exclude those items that disturbed the factor structure because the main aim of factor analysis is to acquire a set of theoretically meaningful factors with easy interpretation and accounts for the bulk of the variance (Hair et al., 2003). Majority of the papers do not explain how the items were deleted (Lu and Marlow, 1999, Pantouvakis, 2006, Jenssen and Randøy, 2006). Most of the papers simply mention why some items were deleted and then present the final factor structure. However, when one item is deleted, the whole factor structure will change and when all the problematic items are deleted simultaneously, a completely new factor structure will be attained. Hence, a good idea is to delete the items one at a time, re-run the EFA to see what the factor structure looks like.

In this study, the criteria for exclusion were to look for those items with 1) loadings below the cut-off value of 0.5; and 2) cross loadings (items loading on two factors with loadings above 0.4 were counted as cross-loaded items). While it was decided to delete one item at a time, it was not clear which sequence to follow. Hence, the researcher tried three different conditions and chose the one which caused fewer number of item deletion with a satisfactory and interpretable factor solution. Thoughtful researcher judgements should be used to decide the best sequence (Henson and Roberts, 2006). In the first condition, the sequence was to first delete the items with loadings below the cut-off value of 0.5 (Hair et al., 2003, Field, 2013) and then look for the items with cross loadings. The second condition was to first delete the items with cross-loadings and then look for the items with loadings below the cut-off values. The third condition did not follow a particular sequence because the decision to exclude the items was aimed at achieving a satisfactory factor structure with justifiable interpretation. After trying all three procedures, the factor structure acquired from the third condition was selected as the number of item deletion was fewer from this procedure. It is noteworthy that in all the three procedures, the major problematic items were the same.

The first factor analysis resulted in a factor structure where *Item 7* loaded on Factor 17 with factor loading less than 0.5 (EFA 1). EFA was run again without *Item 7* which resulted in a slightly different factor structure. The factor structure resulted with two items (*Item 39* = 0.474 and *Item 3* = -473) with loadings below 0.5 (EFA 2). After deleting *Item 3* and running the EFA, *Item 39* still remains the one with the factor loading less than 0.5. However, the new factor structure resulted in *Item 2* loading positively on one factor and negatively on the other (EFA 3). This item seemed problematic in the sense that it cross-loaded negatively on one factor. Hence, it was decided to exclude this item first. The EFA output after removing *Item 2* resulted in two items, *Item 37* and *Item 43* each loading on two factors with almost same factors loadings (*Item 37* = 0.488 and 0.487; and *Item 43* = 0.503 and 0.506) (EFA 4). *Item 37* was considered for exclusion and the EFA was run again. In the new factor structure, *Item 43* still loaded on two factors with loadings = 0.490 and 0.500 (EFA 5) and thus, was deleted. Now, *Item 39* loaded on Factor 2 with loading less than 0.5 and also cross-loaded on Factor 3 (EFA 6). After deleting *Item 39*, the EFA extracted 16 factors and resulted in a factor structure with no cross-loadings. However, there was one item (*Item 8*) with loading below the cut-off value (EFA 7). Since the aim was to include only those items with loadings greater than 0.5, it was decided to delete *Item 8*. The EFA result after deleting *Item 8* yielded a factor solution with no cross-loadings and all the item loadings greater than 0.5 (EFA 8).

In order to name the factors, the factor structure was compared with the survey items. While all the loadings made sense, there were two items, *Item 51* and *Item 52* which needed further consideration. *Item 51* "We face uncertainties due to changing customer demand" loaded with items that were related to personal connection between supply chain partners and hence, did not make much sense. However, *Item 52* "We face difficult situations due to supply uncertainties" negatively loaded with items related to trust which quite made sense. It is likely that supply chain participants may find it too risky to trust suppliers with high uncertainties. Therefore, it was decided to delete *Item 51* while retaining *Item 52*.

The remaining factors were analysed one more time to obtain a satisfactory and interpretable factor structure (EFA 9 presented in Table 2). The Kaiser-Meyer Olkin measure of sampling adequacy (KMO) was 0.628 (> 0.50) (Hair et al., 1998) which was acceptable and Bartlett's test of sphericity was significant ($p < 0.001$) meaning that the correlations between variables are significantly different from zero (Field, 2013). After 9 repetitions and deleting 8 items, the final factor solution extracted 16 factors that accounted for 75.9% of the variance and were named based on the factors identified from the literature. While several authors suggest to have at least 3 items under each factor (Stage et al., 2004, Tabachnick and Fidell, 2007, Meyers et al., 2013), supply network configuration and market orientation scale had 2 items each. After the satisfactory factor structure was decided, EFA was run again in order to calculate the factor structure by selecting Anderson-Rubin method under the tab 'scores' in SPSS. The calculation of factor score using the Anderson-Rubin method ensured that the factors are uncorrelated which is an important assumption for conducting multiple regression analysis.

7. Recommendations for Future Research

Based on the review of the maritime related articles, the following recommendations are made for future researchers aiming to conduct EFA in their studies:

- It is advisable to report the methodological decisions that include suitability of the data for factor analysis, factor extraction and retention criteria, rotation, number of factors extracted and the percentage of variance explained.

- Researchers should use their subjective judgment to decide the final factor structure such that it captures the necessary information to answer the research question without losing much information.
- While the problematic items that disturb the interpretability of the solution can be deleted, the aim should be to delete as few items as possible. Moreover, the reason for the deletion should be noted.
- Trial-and-error method should be employed for selecting the final factor structure. Since the deletion of one item changes the factor structure, it is advisable to re-run the EFA couple of times, deleting different items, one at a time. This will allow the researcher to check different factor structures and select the one that is more appropriate.
- While factor loadings of 0.7 or greater are considered as practically significant, factor loadings of 0.5 or greater can be considered as adequate indicators for that factor (Comrey and Lee, 1992, Hair et al., 1998, Tabachnick and Fidell, 2007).
- The EFA output will show all the items loading on all the factors. However, the factor loadings on different factors will be different (an item might load significantly on one factor while its loading might be low or negligible on the other). It is an important decision to select a threshold value to consider an item to have multiple-loadings. For example: Considering 0.4 as a threshold value, an item will be identified as a cross-loading item if it loads at 0.4 or higher on two or more factors.
- While some researchers, in case of multiple-loadings, decide to delete the item that loads on more than one item (> 0.4), some researchers choose the factor on which the item loads with highest loading. Despite of what decision is taken, from the readers' perspective, it is preferable to explicitly justify your decision.

8. Conclusion

EFA has been applied by many researchers working in the maritime sector. It is a widely used tool in maritime studies as most of the factors used cannot be measured directly and hence are measured indirectly through indicator variables. In many cases, the details of applying EFA are not sufficient for the readers to understand the interpretation made by the researchers or to make their own independent interpretations. Moreover, there are some shipping-related issues such as port performance, port service quality, quality management in the shipping industry and container development strategies that require the use of EFA. This motivated the authors to review maritime-related journals to find out how EFA has been carried out.

This paper aimed to provide explicit information for future researchers with basic knowledge of EFA on how an exploratory factor analysis can be carried out appropriately. To achieve this aim, 35 papers from four maritime journals were reviewed which comprised of respondents from a variety of maritime fields such as liner shipping companies/agencies, freight forwarders, port authorities, port logistics companies, cruise travellers, ship owners, terminal operators, port managers/supervisors and shipping academics.

While there are no stringent rules to follow while conducting an EFA, it is imperative that a researcher makes permissible and interpretable decisions. The methodological decisions at each point should also be made carefully as they can have a substantial impact on the results and their interpretation. The review of the 35 articles and the example that used EFA demonstrated that EFA can result in an infinite number of solutions depending on the researchers' subjective judgement. Researchers used different criteria, such as deleting items with loadings less than 0.4 or cross-loadings over 0.4, to select the final factor structure depending on their research objectives. However, it is imperative that their decision to retain or delete an item and to select the final solution makes sense. Moreover, researchers should provide sufficient information to allow readers to evaluate the analysis. However, the majority of the reviewed papers failed to provide important information related to the use of EFA and the process of reaching the final structure. Some papers deleted items with no justification while others ignored cross-loaded items without discussing it further. Moreover, most of the papers have not discussed how the items were deleted either simultaneously or one at a time. Inappropriate criteria or approach to delete/retain factors in EFA will significantly affect the quality of the final structure, thus, the accuracy and reliability of research findings.

This study suggested two criteria for item exclusion and encouraged researchers to try three different sequence of item deletion and select the one that results in less number of deletions. The example showed that deleting a single item from the EFA output and running it again will result in a different solution. It recommends future researchers to practice trial-and-error method which is characterised by repeatedly running the EFA with different combinations of items. Hence, it is recommended not to delete all the problematic items at once. Deleting the items one at a time will aid the researcher to see different outputs and then select the one that best suits the study. In addition, this technique may reduce the number of deletions as opposed to deleting all the problematic items in one go.

References

Ahire, S. L. & Devaraj, S., (2001), "An empirical comparison of statistical construct validation approaches", *IEEE Transactions on Engineering Management, Vol.* 48, No. 3**,** pp. 319-329.

Bae, H.-S., (2012), "The Effect of Market Orientation on Relationship Commitment and Relationship Effectiveness of Port Logistics Firms", *The Asian Journal of Shipping and Logistics, Vol.* 28, No. 1**,** pp. 105-134.

Bae, H.-S. & Ha, M.-S., (2014), "The Moderating Effects of Internal Orientation and Market Orientation on the Relationships between Commitment and Transportation Service: An Approach to International Freight Forwarders", *The Asian Journal of Shipping and Logistics, Vol.* 30, No. 2**,** pp. 121-153.

Bandara, Y. M., Nguyen, H.-O. & Chen, S.-L., (2016), "Influential factors in the design of port infrastructure tariffs", *Maritime Policy & Management, Vol.* 43, No. 7**,** pp. 1-13.

Bhattacharya, Y., (2015), "Employee Engagement as a Predictor of Seafarer Retention: A Study among Indian Officers", *The Asian Journal of Shipping and Logistics, Vol.* 31, No. 2**,** pp. 295-318.

Byrne, B. M., (2010), *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming,* New York, Routledge.

Cerit, A. G., (2000), "Maritime Transport as an Area of Competitive Advantage in International Marketing", *International journal of maritime economics, Vol.* 2, No. 1**,** pp. 49-67.

Chang, Y.-T., Liu, S.-M., Park, H. & Roh, Y., (2016), "Cruise traveler satisfaction at a port of call", *Maritime Policy & Management, Vol.* 43, No. 4, pp. 483-494.

Cheng, T. C. E. & Choy, P. W. C., (2007), “Measuring success factors of quality management in the shipping industry”, *Maritime Economics & Logistics, Vol.* 9, No. 3, pp. 234-253.

Cheng, T. C. E. & Choy, P. W. C., (2013), “A study of the relationships between quality management practices and organizational performance in the shipping industry”, *Maritime Economics & Logistics, Vol.* 15, No. 1, pp. 1-31.

Comrey, A. L. & Lee, H. B., (1992), *A First Course in Factor Analysis,* Hillsdale, NJ, Lawrence Erlbaum Associates.

Cortina, J. M., (1993), “What is coefficient alpha? An examination of theory and applications”, *Journal of Applied Psychology, Vol.* 78, No. 1, pp. 98-104.

Costello, A. B. & Osborne, J. W., (2005), “Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis”, *Practical Assessment Research & Evaluation, Vol.* 10, No. 7, pp. 1 - 9.

Dahl, Ø., Fenstad, J. & Kongsvik, T., (2014), “Antecedents of safety-compliant behaviour on offshore service vessels: a multi-factorial approach”, *Maritime Policy & Management, Vol.* 41, No. 1, pp. 20-41.

Distefano, C., Zhu, M. & Mindrila, D., (2009), “Understanding and using factor scores: Considerations for the applied researcher”, *Practical Assessment, Research & Evaluation, Vol.* 14, No. 20, pp. 1-11.

Du, T. C., Lai, V. S., Cheung, W. & Cui, X., (2012), “Willingness to share information in a supply chain: A partnership-data-process perspective”, *Information & Management, Vol.* 49, No. 2, pp. 89-98.

Esmer, S., Nguyen, H.-O., Bandara, Y. M. & Yeni, K., (2016), “Non-Price Competition in the Port Sector: A Case Study of Ports in Turkey”, *The Asian Journal of Shipping and Logistics, Vol.* 32, No. 1, pp. 3-11.

Fabrigar, L. R., Wegener, D. T., Maccallum, R. C. & Strahan, E. J., (1999), “Evaluating the use of exploratory factor analysis in psychological research”, *Psychological Methods, Vol.* 4, No. 3, pp. 272-299.

Fenstad, J., Dahl, Ø. & Kongsvik, T., (2016), “Shipboard safety: exploring organizational and regulatory factors”, *Maritime Policy & Management, Vol.* 43, No. 5, pp. 1-17.

Field, A., (2013), *Discovering Statistics Using IBM SPSS Statistics,* London, Sage Publications Ltd.

Ford, J. K., Maccallum, R. C. & Tait, M., (1986), “The application of exploratory factor analysis in applied psychology: A critical review and analysis”, *Personnel Psychology, Vol.* 39, No. 2, pp. 291-314.

Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. C., (1998), *Multivariate Data Analysis,* New Jersey, Prentice Hall.

Hair, J. F., Babin, B., Money, A. H. & Samouel, P., (2003), *Essentials of Business Research Methods,* USA, John Wiley & Sons.

Hayton, J. C., Allen, D. G. & Scarpello, V., (2004), “Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis”, *Organisational Research Methods, Vol.* 7, No. 2, pp. 191-205.

Henson, R. K. & Roberts, J. K., (2006), “Use of exploratory factor analysis in published research - Common errors and some comment on improved practice”, *Educational and Psychological Measurement, Vol.* 66, No. 3, pp. 393-416.

Jenssen, J. I. & Randøy, T., (2002), “Factors that promote innovation in shipping companies”, *Maritime Policy & Management, Vol.* 29, No. 2, pp. 119-133.

Jenssen, J. I. & Randøy, T., (2006), “The performance effect of innovation in shipping companies”, *Maritime Policy & Management, Vol.* 33, No. 4, pp. 327-343.

Kieffer, K. M., (1999), “An introductory primer on the appropriate use of exploratory and confirmatory factor analysis”, *Research in the Schools, Vol.* 6, No. 2, pp. 75-92.

Kim, S., Kang, D. & Dinwoodie, J., (2016), “Competitiveness in a Multipolar Port System: Striving for Regional Gateway Status in Northeast Asia”, *The Asian Journal of Shipping and Logistics, Vol.* 32, No. 2, pp. 119-125.

Lai, K.-H., Edwin Cheng, T. C. & Yeung, A. C. L., (2004), “An empirical taxonomy for logistics service providers”, *Maritime Economics & Logistics, Vol.* 6, No. 3, pp. 199-219.

Lirn, T.-C., Lin, H.-W. & Shang, K.-C., (2014), “Green shipping management capability and firm performance in the container shipping industry”, *Maritime Policy & Management, Vol.* 41, No. 2, pp. 159-175.

Lu, C.-S., Lai, P.-L. & Chiang, Y.-P., (2016a), “Container terminal employees’ perceptions of the effects of sustainable supply chain management on sustainability performance”, *Maritime Policy & Management, Vol.* 43, No. 5, pp. 597-613.

Lu, C.-S., Lin, C.-C. & Lee, M.-H., (2010), “An Evaluation of Container Development Strategies in the Port of Taichung”, *The Asian Journal of Shipping and Logistics, Vol.* 26, No. 1, pp. 93-118.

Lu, C.-S. & Marlow, P., (1999), “Strategic groups in Taiwanese liner shipping”, *Maritime Policy & Management, Vol.* 26, No. 1, pp. 1-26.

Lu, C.-S., Shang, K.-C. & Lin, C.-C., (2016b), “Examining sustainability performance at ports: port managers’ perspectives on developing sustainable supply chains”, *Maritime Policy & Management, Vol.* 43, No. 8, pp. 909-927.

Lu, C.-S., Shang, K.-C. & Lin, C.-C., (2016c), “Identifying crucial sustainability assessment criteria for container seaports”, *Maritime Business Review, Vol.* 1, No. 2, pp. 90-106.

Maccallum, R. C., Widaman, K. F., Zhang, S. & Hong, S., (1999), "Sample size in factor analysis", *Psychological Methods, Vol.* 4, No. 1**,** pp. 84 - 99.

Meyers, L. S., Gamst, G. & Guarino, A. J., (2013), *Applied Multivariate Research: Design and Interpretation,* California, USA, Sage Publications Inc.

Norzaidi, M. D., Chong, S. C., Murali, R. & Salwani, M. I., (2009), "Towards a holistic model in investigating the effects of intranet usage on managerial performance: a study on Malaysian port industry", *Maritime Policy & Management, Vol.* 36, No. 3**,** pp. 269-289.

Nunnally, J. C., (1967), *Psychometric Theory,* New York, McGraw-Hill.

Oltedal, H. & Wadsworth, E., (2010), "Risk perception in the Norwegian shipping industry and identification of influencing factors", *Marit. Pol. Mgmt., Vol.* 37, No. 6**,** pp. 601-623.

Osborne, J. W. & Costello, A. B., (2009), "Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis", *Pan-Pacific Management Review, Vol.* 12, No. 2**,** pp. 131-146.

Paixão Casaca, A. C. & Marlow, P. B., (2009), "Logistics strategies for short sea shipping operating as part of multimodal transport chains", *Maritime Policy & Management, Vol.* 36, No. 1**,** pp. 1-19.

Pantouvakis, A., (2006), "Port-Service Quality Dimensions and Passenger Profiles: An Exploratory Examination and Analysis", *Maritime Economics & Logistics, Vol.* 8, No. 4**,** pp. 402-418.

Pantouvakis, A., Chlomoudis, C. & Dimas, A., (2008), "Testing the SERVQUAL scale in the passenger port industry: a confirmatory study", *Maritime Policy & Management, Vol.* 35, No. 5**,** pp. 449-467.

Pantouvakis, A. & Psomas, E., (2016), "Exploring total quality management applications under uncertainty: A research agenda for the shipping industry", *Maritime Economics & Logistics, Vol.* 18, No. 4**,** pp. 496-512.

Pantouvakis, A. M., (2007), "Who pays the ferryman? An analysis of the ferry passenger's selection dilemma", *Maritime Policy & Management, Vol.* 34, No. 6**,** pp. 591-612.

Peterson, R. A., (2000), "A meta-analysis of variance accounted for and factor loadings in exploratory factor analysis", *Marketing Letters, Vol.* 11, No. 3**,** pp. 261-275.

Sadovaya, E. & Thai, V. V., (2015), "Impacts of Implementation of the Effective Maritime Security Management Model (EMSMM) on Organizational Performance of Shipping Companies1", *The Asian Journal of Shipping and Logistics, Vol.* 31, No. 2**,** pp. 195-215.

Stage, F. K., Carter, H. C. & Nora, A., (2004), "Path analysis: An introduction and analysis of a decade of research", *The Journal of Educational Research, Vol.* 98, No. 1**,** pp. 5-13.

Tabachnick, B. G. & Fidell, L. S., (1996), *Using Multivariate Statistics,* New York, Harper Collins,.

Tabachnick, B. G. & Fidell, L. S., (2007), *Using Multivariate Statistics,* USA, Pearson Education Inc.

Thai, V. V., Tay, W. J., Tan, R. & Lai, A., (2014), "Defining Service Quality in Tramp Shipping: Conceptual Model and Empirical Evidence", *The Asian Journal of Shipping and Logistics, Vol.* 30, No. 1**,** pp. 1-29.

Tinsley, H. E. & Tinsley, D. J., (1987), "Uses of factor analysis in counseling psychology research", *Journal of counseling psychology, Vol.* 34, No. 4**,** pp. 414.

Triantafylli, A. A. & Ballas, A. A., (2010), "Management control systems and performance: evidence from the Greek shipping industry", *Marit. Pol. Mgmt., Vol.* 37, No. 6**,** pp. 625-660.

Tsai, C.-L., (2014), "The Organizational Climate and Employees' Job Satisfaction in the Terminal Operation Context of Kaohsiung Port1", *The Asian Journal of Shipping and Logistics, Vol.* 30, No. 3**,** pp. 373-392.

Wen, C.-H. & Lin, W.-W., (2016), "Customer segmentation of freight forwarders and impacts on the competitive positioning of ocean carriers in the Taiwan–southern China trade lane", *Maritime Policy & Management, Vol.* 43, No. 4**,** pp. 420-435.

Yang, C.-S., (2016), "Evaluating the use of alternative maritime power in Taiwan", *Maritime Business Review, Vol.* 1, No. 3**,** pp. 208-224.

Yuen, K. F. & Thai, V., (2016), "Barriers to supply chain integration in the maritime logistics industry", *Maritime Economics & Logistics, Vol.* No.**,** pp.

Zikmund, W. G., Babin, B. J., Carr, J. C. & Griffin, M., (2010), *Business Research Methods,* USA, CENGAGE Learning.

Appendices

Appendix 1: EFA Final Output

Item Description	Item	Factor Loading	Eigen Value	% of Variance
Interaction Routines				
Our company and our partners meet regularly to discuss *market condition.*	Item 47	0.803		
Our company and our partners meet regularly to discuss *mutual goals and objectives.*	Item 46	0.801		
Our company and our partners meet regularly to discuss *quality improvement.*	Item 48	0.765	7.988	15.976
We have collaborative relationship with our partners.	Item 50	0.655		
Our company makes joint plans with our partners	Item 49	0.579		

Item Description	Item	Factor Loading	Eigen Value	% of Variance
National Culture				
National culture has affected the amount of information we share with our partners.	Item 57	0.921		
National culture has affected the way we communicate with our partners.	Item 56	0.912	3.762	7.524
National culture has affected our relationships with our international business partners.	Item 58	0.844		
Organisational Compatibility				
Our company and our partners have *similar views towards inter-organisational relationship.*	Item 14	0.703		
Our company and our partners have *similar views towards information sharing.*	Item 13	0.703	3.270	6.541
We gain mutual benefits from the relationship with our partners.	Item 38	0.688		
Our company and our partners have *similar goals and objectives.*	Item 12	0.661		
Information Quality				
Our partners provide us with timely information.	Item 35	0.850		
Our partners provide us with easy-to-understand information.	Item 36	0.844	2.564	5.128
Our partners provide us with useful information.	Item 34	0.826		
Government Support				
The government has enforced laws/regulations that provide stable and reliable conditions for business operations.	Item 53	0.905		
Government policies have increased our confidence to establish collaborative relationships with our partners.	Item 54	0.884	2.431	4.862
Government policies support the development of information technology.	Item 55	0.738		
Incentives				
We offer *incentives* to our partners to provide improved products/service.	Item 28	0.852		
We offer *incentives* to our partners to contribute to increasing our profits.	Item 30	0.835	2.382	4.764
We offer *incentives* to our partners to provide us with useful information.	Item 29	0.716		
Project Payoff				
Our company will invest in information sharing with our partners if *the costs and benefits are shared between both companies*.	Item 24	0.777		
Our company will invest in information sharing with our partners if *the outcome is immediate*.	Item 23	0.747	2.057	4.113
Our company will invest in information sharing with our partners if *the costs are high but the outcome is valuable*.	Item 22	0.695		
Commitment				
We intend to strengthen our relationship with our partners.	Item 5	0.861		
We intend to continue the relationship with our partners for a long term.	Item 4	0.816	1.960	3.919
Both sides in the relationship make decisions that are mutually beneficial.	Item 6	0.701		
Personal Connection				
Personal connections with our partner companies are an added advantage in business decision making.	Item 10	0.824		
Personal connections play an important role in our business.	Item 11	0.759	1.790	3.580
The owner/manager of our company attends the social functions organised by the owner/manager of our partner companies.	Item 9	0.685		
Monitoring				
Our company monitors our partners to detect whether they have provided any incorrect information.	Item 26	0.802		
Our company monitors our partners to detect their wrongful actions for personal benefits.	Item 27	0.783	1.723	3.447
Our company monitors our partners to detect whether they comply with established agreements.	Item 25	0.705		
Information Technology				
We share information with our partners via *online marketing*.	Item 31	0.826		
We share information with our partners via *electronic catalogues*.	Item 32	0.810	1.623	3.245
We share information with our partners via *bar coding/automatic identification system.*	Item 33	0.682		
Legal Contract				
Contracts will hinder the development of a good business relationship.	Item 41	0.870		
Contracts will limit the communication and information-based operations between our company and our partners.	Item 42	0.754	1.538	3.077
There is no need of contracts in our relationship with our partners.	Item 40	0.713		
Trust				
Our partners have a good overall reputation in the market.	Item 20	0.735		
Our partners have always helped us in need.	Item 1	0.698	1.383	2.767
Our partners do not change their partners very often.	Item 21	0.656		
We face difficult situations due to supply uncertainties.	Item 52	-0.519		
Market Orientation				
Our company is concerned about *competitors' strength.*	Item 19	0.855	1.282	2.564
Our company is concerned about *competitors' market position.*	Item 18	0.851		
Top Management Commitment				
Our top management team considers *information sharing with trading partners* to be important to enhance supply chain performance.	Item 16	0.791	1.120	2.240
Our top management team considers *relationships with trading partners* to be important to enhance supply chain performance.	Item 15	0.762		

Item Description	Item	Factor Loading	Eigen Value	% of Variance
Our top management team considers *managerial ties with the top executives of our partner companies* to be important to enhance supply chain performance.	Item 17	0.534		
Supply Network Configuration				
Our indirect supply chain partners are of no concern to us.	Item 45	0.852	1.054	2.107
We never deal with our indirect supply chain partners.	Item 44	0.837		
Total Variance Explained (%)				**75.853**

Appendix 2: Eight EFA Outputs

EFA 1

Rotated Component Matrix[a]

	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.821																
Item 46	.787																
Item 48	.748																
Item 50	.635																
Item 49	.544	.465															
Item 38		.744															
Item 14		.695															
Item 13		.614															
Item 12		.558															
Item 37		.512		.484													
Item 39		.478															
Item 35			.835														
Item 34			.827														
Item 36			.817														
Item 5				.848													
Item 4				.829													
Item 6				.646													
Item 57					.914												
Item 56					.913												
Item 58					.831												
Item 53						.901											
Item 54						.883											
Item 55						.741											
Item 28							.823										
Item 30							.816										
Item 29							.717										
Item 20								.756									
Item 21								.683									
Item 1								.607									
Item 2								.603									-.424
Item 10									.815								
Item 11									.722								
Item 9									.701								
Item 24										.755							
Item 22										.727							
Item 23										.704							
Item 16											.734						
Item 17											.573						
Item 15											.570						
Item 8											.545						
Item 27												.810					
Item 26												.758					
Item 25												.712					
Item 31													.801				
Item 32													.786				
Item 33													.710				
Item 41														.856			
Item 42														.749			
Item 40														.711			
Item 44															.836		
Item 45															.819		
Item 43											.505				.522		
Item 19																.861	
Item 18																.814	
Item 51																	.755
Item 52																	.502
Item 3																	-.439
Item 7																	

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

a. Rotation converged in 15 iterations.

EFA 2

Rotated Component Matrix[a]																	
	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.821																
Item 46	.789																
Item 48	.746																
Item 50	.641																
Item 49	.550	.458															
Item 38		.740															
Item 14		.706															
Item 13		.619															
Item 12		.575															
Item 37		.509		.485													
Item 39		.474															
Item 35			.843														
Item 36			.831														
Item 34			.822														
Item 5				.848													
Item 4				.833													
Item 6				.648													
Item 56					.915												
Item 57					.915												
Item 58					.829												
Item 53						.902											
Item 54						.883											
Item 55						.740											
Item 28							.828										
Item 30							.816										
Item 29							.717										
Item 10								.816									
Item 11								.724									
Item 9								.703									
Item 20									.766								
Item 21									.715								
Item 1									.580								-.414
Item 2									.534								-.506
Item 24										.751							
Item 22										.729							
Item 23										.701							
Item 16											.757						
Item 17											.589						
Item 15											.586						
Item 8											.516						
Item 31												.809					
Item 32												.787					
Item 33												.706					
Item 27													.813				
Item 26													.760				
Item 25													.706				
Item 41														.866			
Item 42														.747			
Item 40														.709			
Item 44															.841		
Item 45															.822		
Item 43											.492				.526		
Item 19																.858	
Item 18																.812	
Item 51																	.733
Item 52																	.559
Item 3																	-.473

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

a. Rotation converged in 14 iterations.

EFA 3

Rotated Component Matrix[a]

	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.822																
Item 46	.788																
Item 48	.747																
Item 50	.639																
Item 49	.547	.461															
Item 38		.741															
Item 14		.706															
Item 13		.617															
Item 12		.579															
Item 37		.510				.483											
Item 39		.477															
Item 35			.840														
Item 36			.836														
Item 34			.823														
Item 57				.915													
Item 56				.914													
Item 58				.832													
Item 53					.902												
Item 54					.883												
Item 55					.741												
Item 5						.845											
Item 4						.831											
Item 6						.659											
Item 28							.826										
Item 30							.818										
Item 29							.718										
Item 10								.817									
Item 11								.724									
Item 9								.702									
Item 20									.767								
Item 21									.715								
Item 1									.598								
Item 2									.558								-.468
Item 24										.750							
Item 22										.733							
Item 23										.699							
Item 16											.754						
Item 17											.590						
Item 15											.587						
Item 8											.518						
Item 27												.812					
Item 26												.762					
Item 25												.705					
Item 31													.808				
Item 32													.791				
Item 33													.702				
Item 41														.869			
Item 42														.746			
Item 40														.710			
Item 44															.841		
Item 45															.822		
Item 43											.492				.526		
Item 19																.857	
Item 18																.811	
Item 51																	.770
Item 52																	.577

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

a. Rotation converged in 13 iterations.

EFA 4

Rotated Component Matrix[a]

	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.818																
Item 46	.789																
Item 48	.739																
Item 50	.657																
Item 49	.566	.421															
Item 38		.739															
Item 14		.698															
Item 13		.633															
Item 12		.618															
Item 37		.488				.487											
Item 39		.451															
Item 35			.842														
Item 36			.840														
Item 34			.823														
Item 57				.917													
Item 56				.912													
Item 58				.838													
Item 53					.900												
Item 54					.882												
Item 55					.745												
Item 5						.852											
Item 4						.832											
Item 6						.660											
Item 30							.828										
Item 28							.824										
Item 29							.729										
Item 10								.817									
Item 11								.724									
Item 9								.701									
Item 24									.764								
Item 22									.732								
Item 23									.712								
Item 16										.755							
Item 15										.589							
Item 17										.575							
Item 8										.516							
Item 27											.811						
Item 26											.760						
Item 25											.706						
Item 31												.814					
Item 32												.804					
Item 33												.677					
Item 41													.871				
Item 42													.746				
Item 40													.710				
Item 44														.836			
Item 45														.829			
Item 43										.503				.506			
Item 20															.771		
Item 21															.729		
Item 1															.579		
Item 19																.864	
Item 18																.816	
Item 51																	.774
Item 52																	.609

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

a. Rotation converged in 10 iterations.

EFA 5

Rotated Component Matrix[a]																	
	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.817																
Item 46	.790																
Item 48	.738																
Item 50	.664																
Item 49	.575		.415														
Item 35		.844															
Item 36		.842															
Item 34		.823															
Item 38			.710														
Item 14			.709														
Item 13			.656														
Item 12			.646														
Item 39			.426														
Item 57				.917													
Item 56				.911													
Item 58				.838													
Item 53					.901												
Item 54					.883												
Item 55					.743												
Item 30						.828											
Item 28						.821											
Item 29						.728											
Item 5							.860										
Item 4							.833										
Item 6							.675										
Item 10								.811									
Item 11								.732									
Item 9								.717									
Item 24									.764								
Item 22									.758								
Item 23									.702								
Item 16										.765							
Item 15										.605							
Item 17										.594							
Item 8										.487							
Item 31											.812						
Item 32											.805						
Item 33											.674						
Item 41												.870					
Item 42												.746					
Item 40												.712					
Item 27													.824				
Item 26													.770				
Item 25													.706				
Item 44														.834			
Item 45														.832			
Item 43										.490				.500			
Item 20															.779		
Item 21															.722		
Item 1															.562		
Item 19																.876	
Item 18																.835	
Item 51																	.771
Item 52																	.631

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

a. Rotation converged in 10 iterations.

EFA 6

Rotated Component Matrix[a]

	Component																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Item 47	.815																
Item 46	.791																
Item 48	.740																
Item 50	.660																
Item 49	.567	.427															
Item 38		.714															
Item 14		.708															
Item 13		.659															
Item 12		.648															
Item 39		.424	.406														
Item 35			.850														
Item 36			.835														
Item 34			.823														
Item 57				.917													
Item 56				.911													
Item 58				.839													
Item 53					.903												
Item 54					.886												
Item 55					.743												
Item 30						.830											
Item 28						.822											
Item 29						.729											
Item 5							.862										
Item 4							.833										
Item 6							.674										
Item 10								.820									
Item 11								.729									
Item 9								.705									
Item 22									.757								
Item 24									.754								
Item 23									.694								
Item 31										.816							
Item 32										.811							
Item 33										.670							
Item 41											.870						
Item 42											.748						
Item 40											.713						
Item 27												.829					
Item 26												.772					
Item 25												.697					
Item 16													.762				
Item 17													.615				
Item 15													.600				
Item 8													.518				
Item 19														.876			
Item 18														.837			
Item 20															.780		
Item 21															.726		
Item 1															.538		-.400
Item 45																.856	
Item 44																.822	
Item 51																	.771
Item 52																	.633

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

a. Rotation converged in 10 iterations.

EFA 7

Rotated Component Matrix[a]

	Component															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Item 47	.828															
Item 46	.812															
Item 48	.730															
Item 50	.652															
Item 49	.574															
Item 57		.918														
Item 56		.911														
Item 58		.838														
Item 13			.710													
Item 14			.704													
Item 12			.657													
Item 38			.655													
Item 10				.773												
Item 9				.709												
Item 11				.692												
Item 18				.585												
Item 19				.555												
Item 35					.844											
Item 36					.842											
Item 34					.829											
Item 53						.897										
Item 54						.884										
Item 55						.747										
Item 30							.832									
Item 28							.812									
Item 29							.730									
Item 24								.763								
Item 23								.744								
Item 22								.695								
Item 5									.856							
Item 4									.830							
Item 6									.687							
Item 27										.765						
Item 26										.760						
Item 25										.758						
Item 16											.812					
Item 17											.601					
Item 15											.556					
Item 8											.496					
Item 31												.809				
Item 32												.808				
Item 33												.672				
Item 41													.870			
Item 42													.749			
Item 40													.719			
Item 20														.786		
Item 21														.653		
Item 1														.617		
Item 45															.854	
Item 44															.829	
Item 51																.738
Item 52																.721

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

a. Rotation converged in 21 iterations.

EFA 8

Rotated Component Matrix[a]

	Component															
	0	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Item 47	.819															
Item 46	.806															
Item 48	.741															
Item 50	.645															
Item 49	.569															
Item 57		.923														
Item 56		.915														
Item 58		.840														
Item 13			.702													
Item 14			.696													
Item 38			.689													
Item 12			.657													
Item 35				.846												
Item 36				.840												
Item 34				.829												
Item 53					.898											
Item 54					.885											
Item 55					.748											
Item 28						.844										
Item 30						.842										
Item 29						.735										
Item 24							.773									
Item 23							.762									
Item 22							.620									
Item 10								.798								
Item 9								.684								
Item 11								.650								
Item 51								.541								
Item 5									.863							
Item 4									.817							
Item 6									.698							
Item 31										.827						
Item 32										.798						
Item 33										.686						
Item 26											.801					
Item 25											.735					
Item 27											.718					
Item 41												.871				
Item 42												.751				
Item 40												.715				
Item 18													.814			
Item 19													.803			
Item 20														.742		
Item 1														.706		
Item 21														.632		
Item 52														-.505		
Item 16															.760	
Item 15															.760	
Item 17															.540	
Item 45																.856
Item 44																.830

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

a. Rotation converged in 14 iterations.