Exploratory factor analysis in transportation research: current practices and recommendations

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Exploratory factor analysis (EFA) is a widely used statistical method in traffic and transportation research, particularly for the development and validation of measurement instruments. This article critically examines current practice in conducting and reporting EFA in published transportation studies. One hundred and eighty papers published between 2016 and 2018 were examined, of which one hundred and nine were included in the present study after applying eligibility criteria. The review suggests that the quality of EFA reported in the field is routinely poor: (a) researchers fail to provide sufficient information to be able to adequately assess the appropriateness and quality of both the input data and the reported output; and (b) the decisions underlying the choices of EFA methods are not justified and rely mostly on procedures advised against, particularly the Little-Jiffy approach. In summary, a significant gap between current practice and experts' recommendations exists. We provide some guidelines that may help in conducting, reporting and reviewing EFA in transportation research.

Keywords: transportation; research methods; multivariate analysis; exploratory factor analysis

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1. Introduction

Exploratory factor analysis (EFA) is a multivariate statistical method aimed at explaining the relationships among a set of observed variables (or items) in terms of a smaller number of unobservable (latent) variables referred to as factors (Lawley & Maxwell, 1963). This method can be used for a variety of purposes, but mainly for: (a) reducing and summarizing the information contained in the observed variables, and (b) identifying meaningful theoretical constructs that are responsible for the relationships observed among the observed variables (Goldberg & Velicer, 2006). In both cases, the resulting factors can then be included as independent variables in regression models or other multivariate analyses, a quite common practice.

EFA is a multi-step process that requires several statistical and methodological decisions (Howard, 2016). These decisions are primarily concerned with the type of correlation matrix, the factor extraction method, the factor retention method, and the factor rotation method. Over the last years psychometricians have been continuously developing new methods, resulting in a number of improvements to EFA (e.g., Golino & Epskamp, 2017; Preacher, Zhang, Kim, & Mels, 2013; Timmerman & Lorenzo-Seva, 2011). However, these advances have not always been implemented in practice and, in fact, studies have consistently shown the presence of outdated methods and misuse of EFA (Goretzko, Pham, & Bühner, 2019; Izquierdo, Olea, & Abad, 2014). A persistent problem is the extended use of the “Little-Jiffy” approach (Kaiser & Rice, 1974), which involves the use of principal component analysis (PCA) for factor extraction, Kaiser’s eigenvalues-greater-than-one rule for factor-retention, and orthogonal Varimax for factor rotation. As we discuss in the next section, these methods have many drawbacks and for this reason several researchers have strongly discouraged their use (e.g., Costello & Osborne, 2005; Lloret-Segura, Ferreres-Traver, Hernández-Baeza, & Tomás-Marco, 2014). Surprisingly, however, the use of Little-Jiffy is still highly frequent (Henson & Roberts, 2006; Howard, 2016; Sakaluk & Short, 2017), suggesting that many researchers are either unfamiliar with recent developments in the field or disconcerted by the various methods now available for conducting EFA, leading them to resolve their uncertainty by automatically applying the default options present in popular statistical software (Izquierdo et al., 2014). Both instances can lead to inappropriate or erroneous decisions that compromise the integrity of the EFA results.

EFA is commonly reported in transportation studies, typically used, albeit not exclusively, for the assessment of the dimensionality of psychosocial and behavioral measures. Indeed, the factor structure underlying many of the most popular self-report measures in road safety, such as the Driver Behavior Questionnaire (Reason Manstead, Stradling, Baxter, & Campbell, 1990), the Multidimensional Driving Style Inventory (Taubman-Ben-Ari, Mikulincer, & Guillath, 2004), the Driving Anger Expression Inventory (Deffenbacher, Lynch, Oetting, & Swaim, 2002) or the Behavior of Young Novice Drivers Scale (Scott-Parker, Watson, King, & Hyde, 2012) is based on EFA. Despite its widespread use, studies critically examining current EFA practices in traffic and transportation studies are lacking. We were able to identify only one study which examines the use of EFA in maritime journals (Maskey, Fei, & Nguyen, 2018). The findings of this review are in line with studies in other fields suggesting an important gap between current recommendations and the choices made by researchers.

The present review examines common practices in conducting and reporting EFA in transportation studies. It also provides an overview of current recommendations for best practices. The intention is not to undertake a detailed analysis of EFA procedures, which lies beyond the scope of this review, but to provide helpful guidelines for researchers regarding (a) sample size, (b) selection of statistical software, (c) type of correlation matrix to be analyzed, (c) estimation method (extraction), (d) number of factors (retention method), (e) factor rotation method, and (f) reporting of the pattern loading matrix. In the last section we provide a summary of conclusions and recommendations of use in conducting, reporting and reviewing EFA in transportation research.

1.1. The present literature review

Figure 1 summarizes the literature search and selection criteria. The literature search was conducted using the Transport Research International Documentation (TRDI) database, the most comprehensive bibliographic resource on transportation research (Transportation Research Board, 2020). A search using the keyword "factor analysis" in all fields yielded a total of 180 references for the period between January 2016 and July 2018. Forty documents were excluded after the abstract screening (thirty-four were conference proceedings, two were literature review papers, and two had full text in the Japanese language). The remaining full-text articles were then assessed for eligibility by the authors. Of these, a further fifty-eight articles were excluded because they did not focus on transportation issues or they did not include EFA. The final sample comprised eighty-two articles published in different journals (Table 1), most of them addressing psychological and behavioral factors (human factors). When several EFAs were applied to different subsets of data in the same article, each EFA was recorded and analyzed separately. To assess consistency in data coding, a random subsample of n = 23 papers was independently analyzed by two researchers. Almost perfect agreement was observed among them (mean value of Cohen's kappa across the different variables was 0.91).

The review was focused on the following main topics: (a) sample size, (b) software used, (c) preliminary checks: factorability and choice of the correlation matrix, (d) fitting the

EFA model (extraction), (e) criteria for choosing the number of factors, (f) transformation (rotation) methods, and (g) reporting of the EFA (pattern loading matrix). For each topic, we provide a conceptual introduction and review of current recommendations, along with a description of common practices in transportation research.

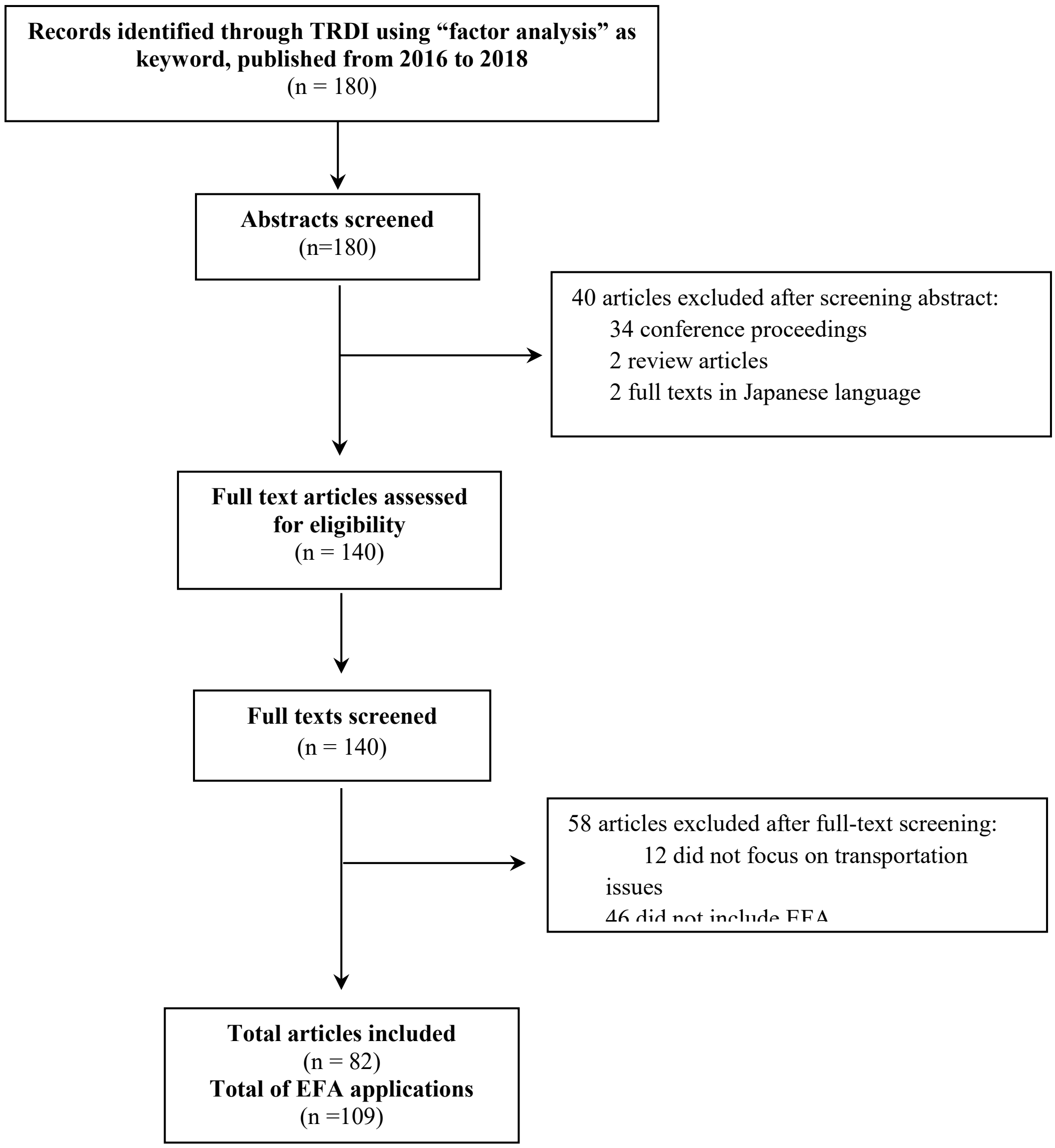

Figure 1. Literature search and selection criteria.

	n	%
Journal		
Transportation Research Part A: Policy and Practice	20	18.3
Transportation Research Part F: Traffic Psychology and Behavior	14	12.8
Transportation Research Part D: Transport and Environment	9	8.3
Accident Analysis & Prevention	5	4.6
Transport Policy	5	4.6
Journal of Modern Transportation	4	3.7
Journal of Transport Geography	4	3.7
Transportation Research Record	4	3.7
Travel Behaviour and Society	4	3.7
Maritime Policy & Management	3	2.8
Traffic Injury Prevention	3	2.8
Others (with less than three articles)	34	31.2
Variables		
Human factors	96	88.1
Environmental and Infrastructure factors	10	9.2
Others (e.g., vehicular factors)	3	2.7
Discipline of the authors		
Psychology	18	16.5
Engineering & technology	40	36.7
Business, economics and management	24	22.0
Geography, urbanism, and environmental sciences	10	9.2

Health sciences	2	1.8
Various disciplines	15	13.8

Table 1. Articles using Exploratory Factor Analysis (EFA) by journal, variable type, and discipline of the authors.

2. Use of EFA in transportation research

2.1. Sample size

One of the most important decisions during the design phase of transportation research concerns the sample size required to perform an EFA. There are two different approaches addressing this issue: (1) one suggests a minimum sample size and (2) one recommends a specific ratio of participants per variable or item (n:p). In the former case, suggestions for minimum sample size are variable, ranging from 150 to 500 participants (Comrey & Lee, 1992; MacCallum, Widaman, Zhang, & Hong, 1999; Wirth & Edwards, 2007). In the latter case, several guidelines have been proposed, ranging from 5:1 to 20:1 (Gorsuch, 1983; Hair, Black, Babin, Anderson, & Tatham, 2006; Velicer & Fava, 1998). In either case, it should be noted that determining the adequate sample size for EFA is a complex decision, depending on many factors such as the type of correlation matrix used, the number of variables per factor, and the commonalities of the variables (Beavers et al., 2013; Mundfrom & Shaw, 2005). For this reason there can be no strict rule to follow, although a minimum of 200 participants is often recommended, particularly when there are high commonalities (greater than .70) and several variables per factor (at least six). In cases with low commonalities (around .30) and low number of variables per factor, on the other hand, a sample size of 400 or even 500 would be necessary to obtain stable results (Lloret-Segura et al., 2014).

In summary, there is no a universal rule for sample size, but it should be kept in mind that EFA is a large-sample procedure (Costello & Osborne, 2005) and large samples are preferable whenever possible. Following current recommendations (e.g., Ferrando & Anguiano-Carrasco, 2010; Howard, 2016; Pérez & Medrano, 2010) we suggest a sample size of at least n = 200, and an n:p ratio of at least 10, whichever is greater. The requirement for a larger sample size is particularly relevant when polychoric correlations are used, since estimations tend to be more unstable than the product-moment correlation (Holgado-Tello, Chacón-Moscoso, Barbero-García, & Vila-Abad, 2010).

Table 2 summarizes the sample sizes and n:p ratio observed in the revised studies. Overall, most articles meet the proposed standards regarding the minimum sample size (68.8%) and nearly one-third of the studies employ large samples (*n* > 600). The n:p ratio was at least 10 in the 74.4% of the articles.

	n	%
Sample size (n)		
< 100	8	7.3
100-200	26	23.9
201-300	12	11.0
301-600	28	25.7
> 600	32	29.3
Unspecified	3	2.8
Sample size/variables ratio (n:p)		
< 5	14	12.8
5-9.9	14	12.8

10-19.9	32	29.3
> 20	42	38.5
could not be calculated	7	6.4
Software used		
SPSS	46	42.2
R	4	3.7
FACTOR	1	0.9
Unspecified	58	53.2

Table 2. Sample size and software used in transportation studies applying EFA (n = 109)

2.2. Statistical software

A second important but often neglected issue in the design phase concerns the choice of statistical software. There are many options available: Mplus (Muthén & Muthén, 2010), FACTOR (Lorenzo-Seva & Ferrando, 2006), LISREL (Jöreskog & Sörbom, 2007), SPSS (IBM Corp, 2012), SAS/STAT (SAS Institute Inc, 2011) and the "Psych" package in R (Mair, 2018), to name a few. It is important to note that choosing one or other of the available alternatives is not trivial, since procedures can differ greatly across software packages (see Lloret-Segura, Ferreres-Traver, & Tomás-Marco, 2017). For instance, FACTOR and Mplus enable researchers to perform EFA using polychoric or product-moment correlation matrices, whereas SPSS includes only the latter. In our view, software for EFA should at the very least include tools to check the data and EFA's adequacy, enable several estimation, retention and rotation methods, and allow different types of correlation matrix to be analyzed. The FACTOR program has been developed specifically for conducting EFA and is perhaps the most complete software for this type of analysis; furthermore, it is user-friendly and freely available to researchers (Ferrando & Lorenzo-Seva, 2017).

Table 2 shows that more than half of the transportation studies reviewed did not report the software used and among those that did, the overwhelming majority used SPSS (90% of the total studies that reported the software). Other recommended programs, such as FACTOR or R, were rarely used. This is worth noting since, as we illustrate next, common EFA methods reported in transportation studies correspond to the default options in SPSS.

2.3. Preliminary checks: factorability and choice of the correlation matrix

The common EFA is a linear model intended for continuous-unlimited variables. However, in most transportation research applications (see Table 3) the model is applied to ordered categorical (ordinal) variables, such as Likert scale items, for which the linear model is theoretically inappropriate for two main reasons: firstly, categorical variables are non-linearly related to the factors; secondly, the factor-variable relationships are attenuated due to categorization. The extent to which these inadequacies are relevant in practice depends mainly on three determinants (Ferrando & Lorenzo-Seva, 2014): the extremeness of the distributions of the variables (skewness), the strength of the factor-variables relationships, and the number of categories. Non-linearity thus becomes more pronounced when the variables are both extreme and strongly related to the factors, while attenuation becomes maximal (other things being equal) in the case of only two categories. The main impact of these inadequacies on the factor results are: (a) differentially biased (attenuated) loading estimates, and (b) distorted goodness-of-fit assessment in the sense that additional, spurious factors of no substantive interest are generally needed for obtaining an acceptable fit (McDonald & Ahlawat, 1974).

	n	%
KMO's values		
.61-.69	5	4.6
.70-.79	10	9.2
.80-.89	23	21.1
.90-1.00	12	11
Unspecified	51	46.8
Provided a KMO' cutoff value (e.g., > .60)	8	7.3
Bartlett's test of sphericity		
Reported*	51	46.8
Did not report	56	51.4
Did not specify the results of the test	1	0.9
Reporting error	1	0.9
Type of variable		
Binary / Dichotomous	1	0.9
Ordered categorical (Likert-type data)	87	79.8
Continuous	11	10.1
Mixture	3	2.8
Unspecified	7	6.4
Type of correlation matrix		
Pearson	4	3.7
Unspecified	105	96.3
Descriptive statistics: central tendency and dispersion		
Reported	42	38.5

Did not report	67	61.5
Descriptive statistics: kurtosis and skewness		
Reported	5	4.6
Did not report	104	95.4

*In all cases significant p-values (p < .05) are reported

Table 3. Preliminary checks of sample's adequacy for EFA, type of variables analyzed and correlation matrix used in transportation studies (n = 109)

A theoretically more appropriate model for ordered categorical variables is non-linear EFA based on the underlying variables approach (UVA; Muthén, 1984), which treats the variables explicitly as ordered-categorical. The basic concepts of ~~the~~ UVA are that (a) ~~there are~~ continuous variables of response strength ~~that~~ underlie the observed ordered-categorical responses, such~~o~~ that the latter~~se observed responses~~ arise as a result of a categorization of the underlying variables at given thresholds, and (b) the standard linear FA model holds for the underlying variables. ~~From a practical viewpoint, t~~The choice between fitting -the linear model ~~fitted~~ directly to the observed responses~~,~~ or to the UVA model~~,~~ in practice means ~~entails~~ fitting the EFA model to the Pearson correlation matrix (linear EFA) or to the polychoric correlation matrix (nonlinear UVA-EFA; see Ferrando & Lorenzo-Seva, 2014).

~~Overall, t~~There is a large body of literature on the appropriateness of either linear EFA or nonlinear UVA-EFA (see Ferrando & Lorenzo-Seva, 2014), and rigid positions are quite common. Our position, however, is that all models are approximations, so the choice of which model is most appropriate should be based on a careful scrutiny of the data to be analyzed. This scrutiny should mainly consider: the size of the sample, the number of response categories, the magnitude of the correlations among the variables, and the mean and skewness of the distributions. Indeed, we recommend against the indiscriminate use of the Pearson matrix (i.e. the linear model) just because it is the default option or the only one available in mainstream programs. To give a clear example, for the case of moderately correlated variables~~,~~ ~~that use~~with five or more categories and~~, with~~ no skewed distributions ~~and~~, ~~which are~~ measured in a medium-to-small sample of, say, 200 individuals, the linear EFA model is a reasonable choice. At the other extreme, the case of binary variables with extreme distributions measured in a large sample calls for the use of the nonlinear UVA-EFA model.

Regardless of the correlation matrix that is finally chosen, a recommendable preliminary step in the analysis is to assess whether there is sufficient correlation among the variables to justify the structural hypotheses imposed by the EFA. We shall denote this type of evidence as factorability of the correlation matrix. Initial evidence of factorability can be obtained by inspecting the magnitude of the correlations among the variables. However, the most common statistics used are global and summarize factorability with a single value. They are: Bartlett's (1950) test of sphericity and the Kaiser-Meyer-Olkin (KMO) sampling adequacy measure (Kaiser & Rice, 1974). Bartlett's test is a global statistic that tests the null hypothesis that the correlation matrix is an identity matrix. Hence, failure to reject this hypothesis means that the variables are essentially uncorrelated, so that no relationships exist for EFA to summarize. If, on the other hand, the test is statistically significant, then there is at least one factor that can be obtained from the data (Everitt & Wykes, 2001). Nevertheless, due to its high sensitivity and dependence on sample size, Bartlett's test tends to be significant with medium and large samples sizes even if correlations are very low (Tabachnick & Fidell, 2013). Thus, Bartlett's test should be interpreted with caution, particularly in the case of large sample sizes. Alternatively, the KMO is an indicator of common variance among the measured variables which is independent of sample size, and ranges from 0 to 1 (Kaiser, 1970). It has been suggested that only KMO values above .60 are acceptable for applying EFA (Dziuban & Shirkey, 1974; Kaiser, 1970). Other authors have proposed more conservative KMO cut-off values of .70 or even .80 (Hoelzle & Mayer, 2013; Hair, Anderson, Tatham, & Black, 1999; Ferrando & Anguiano-Carrasco, 2010). In the present study, values ≥ .70 are considered adequate.

The information necessary to assess the adequacy of the EFA for the data-type and factorability of the correlation matrix was largely absent in the reviewed studies. As can be seen in Table 3, most of them did not report the type of correlation matrix used (96.3%). However, as most of them reported the use of SPSS for the analysis, it can be inferred that Pearson's correlation was generally used as the input matrix. Furthermore, measures of shape distribution were almost always omitted (95.5%), more than half the studies did not report measures of central tendency and variability (61.5%), and the KMO and Bartlett's test were unreported in half or nearly half of the studies (46.8% and 51.4%, respectively). Because of the type of variable usually analyzed (ordered-categorical in 79.8% of cases), one would expect a more careful scrutiny of the data.

2.4. Fitting the EFA model (extraction)

EFA involves making choices in three important areas: in the selection of an estimation procedure (factor extraction method), in deciding the number of factors to retain, and in selecting a rotation method. Table 4 summarizes the choices made in the reviewed studies.

	n	%
Extraction		
Principal Component Analysis (PCA)	63	57.8
Principal Axis Factoring (PAF)	14	12.8
Maximum Likelihood (ML)	5	4.6
Unweighted least squares (ULS)	1	0.9
Unspecified	26	23.9

Number of factor *		
Kaiser’s rule (Eigenvalues > 1)	68	62.4
Cattell's Scree test	19	17.4
Parallel Analysis	5	4.6
Unspecified	22	22.0
Rotation		
Orthogonal	54	49.5
Oblique	24	22.0
Unspecified	27	24.8
Not applicable (unidimensional solutions)	4	3.7

* Each single application of EFA may contain multiple factor retention methods

Table 4. Extraction, retention, and rotation methods used in transportation studies.

From a methodological perspective, EFA is a structural equation model that can be fitted and assessed in the same way as any other model of this type. However, this obvious fact is not generally reflected in EFA applications, which tend to favour the use of approximate (but simpler) procedures at the expense of those that are more theoretically sound. In particular, previous studies suggest that Principal Components Analysis (PCA) is the most common approach for fitting an EFA model (Frías-Navarro & Pascual-Soler, 2012; Norris & Lecavalier, 2010; Roberson, Elliott, Chang, & Hill, 2014). This is in line with our findings showing that PCA was used in 58% of cases and 76% if cases that do not report the estimation method are excluded. PCA, however, is not the correct procedure for the EFA model, rather it is intended to obtain linear composites of observed variables with maximal variance. When used for fitting the EFA model, PCA fails to separate common variance from error variance, and this failure has two potential consequences: (a) upwardly biased loading estimates, and (b) overestimation of the number of common factors (e.g. Ferrando & Anguiano-Carrasco, 2010). These problems are mitigated when there are many observed variables and these variables have small amounts of measurement error, in which case PCA might be a simple and reasonable option. However, this scenario is not usual in EFA applications in which the variables have typically large amounts of error.

When PCA is fitted to a reduced correlation matrix with communality estimates in the main diagonal, the resulting approach is known as principal axis factoring (PAF), a theoretically correct method for fitting the EFA model that separates between common and error variance. PAF can be considered as an "approximate" least-squares EFA-fitting procedure because the communalities used in the diagonal are not the "true" (unknown) communalities. Thus,~~So,~~ depending on the choice of ~~the~~ estimated communalities, the PAF solution may vary, and, more importantly, the reduced correlation matrix may fail to be positive definite; this~~, which,~~, in turn, may lead to improper solutions and/or biased parameter estimates (Lorenzo-Seva & Ferrando, 2020). ~~In spite of~~Despite these shortcomings, ~~however,~~ PAF is nevertheless a ~~defensible~~ justifiable option, especially in analyses in which the reduced correlation matrix is positive definite and which are based on a large number of variables and sample sizes that are not over~~too~~ large~~ sample sizes~~. PAF is also the logical choice when the theoretically superior procedures described below show convergence problems. In the reviewed studies, PAF was the second-most chosen option (12.8%).

"Modern" procedures for fitting the EFA model have three main features: (a) they have a statistical basis that allows standard errors of the parameter estimates and inferential goodness-of-fit statistics to be obtained (although under very restrictive assumptions); (b) they are iterative; and (c) they do not require preliminary commonality estimation. Of these features, (b) can be considered as a potential shortcoming, because it means that the estimation process is more complex and that problems of convergence and improper solutions might appear. However, (a) and (c) are~~,~~ clearly~~,~~ advantages. Feature (c) avoids the indeterminacy and variability due to the particular choice of the communality estimates. Feature (a) provides a rigorous ~~ways for~~means of assessing the salience or relevance of a factor loading (via standard errors) and the goodness of fit of the solution under study, which, in the EFA case, is used for deciding the most appropriate number of common factors.

The main procedures in the group so far discussed are (see e.g. Ferrando & Lorenzo-Seva, 2017): Maximum Likelihood (ML), unweighted least squares (ULS) and weighted least squares (WLS). These procedures have been considerably improved in recent decades and are recommendable options when feasible. The main improved versions available at present are robust procedures that maintain the relative simplicity of the original procedure for estimating the model parameters, but provide corrections to the standard errors~~s~~ and goodness-of-fit statistic, allowing for the assessments described above to be correctly ~~made under~~based on more realistic assumptions. In ~~more detail, in~~ the case of the linear EFA model, the robust corrections are expected to provide correct assessments even when the variables do not follow a multivariate normal distribution. If this model is to be used, then~~,~~ robust maximum likelihood (MLR; Muthén & Muthén, 2010) is ~~a~~ the recommended choice.

In the case of ordered-categorical variables that are to be fitted with the nonlinear UVA-EFA model, ML is not generally recommended, since it does not take into account the data's categorical nature (Barendse, Oort, & Timmerman, 2014; Wirth & Edwards, 2007). Instead, least squares methods such as ULS and WLS have been recommended (Lee, Zhang, & Edwards, 2012). The ULS based on a polychoric correlation matrix has been shown to perform well (Forero, Maydeu-Olivares, & Gallardo-Pujol, 2009) even with small samples and furthermore diminishes the likelihood of improper solutions, such as Heywood cases (Lloret-Segura et al., 2017). Full WLS is, theoretically, the most efficient estimator for ordinal variables, but is only recommended if samples large~~r~~ enough to obtain accurate and stable estimations of model parameters are available (Wirth & Edwards, 2007). Lastly, robust corrections for ULS and WLS (RULS and WLSMV) have proven to work well under different conditions (e.g. different sample sizes and number of categories; Barendse et al., 2014; Li 2016a, 2016b), and are therefore recommendable options.

~~To~~ In sum~~ up~~, selection of one or other of the different methods available for factor extraction should be based on the data type and the shape of the variables distribution. For continuous variables in which the linear EFA model is the chosen option, robust ML is possibly the best choice -unless it gives rise to convergence problems, in which case a computationally simpler method such as ULS or even PAF (~~the~~ computationally the simplest) is preferable. For ordered-categorical variables fitted with the non-linear UVA-EFA model, robust diagonally-weighted WLS or robust ULS are expected to work well except in the limiting case of too many variables and ~~too small~~ samples that are too small. Finally, as discussed earlier, we do not in general recommend ~~in general~~ using PCA when conducting EFA. However, ~~In contrast with these recommendations,~~ our findings suggest that current practices depart considerably from the above recommendations~~are far from optimal in this regard~~. A quarter of the studies reviewed did not report the extraction method and among those that did, the rationale for the decision was almost never provided. ~~In addition~~Furthermore, PCA continues to be the main method of choice.

2.5. Selecting the number of factors

Since the main goal of EFA is to explain the correlations among observed variables in terms of a reduced number of theoretically meaningful factors, deciding the appropriate number of factors to extract is clearly of great relevance. Underestimation (selecting too few factors) and overestimation (selecting too many factors) can have adverse effects on the EFA results. In the former case, the factor pattern loadings may become overly complex and the identified factors therefore difficult to interpret. In the latter case, additional factors are produced without any substantive interpretation (Watkins, 2018).

Previous reviews show that Kaiser's criterion of eigenvalues greater than one remains the most utilized criterion among researchers to select the number of factors (e.g., Conway & Huffcutt, 2003; Maskey et al., 2018). The present findings also show this criterion to be the most used one in transportation research (see table 4). According to this rule, only factors with eigenvalues greater than one are retained. Despite its widespread use, experts agree that the procedure is not recommendable (e.g. Baglin, 2014; Costello & Osborne, 2005) for several reasons. Firstly, its rationale is unclear and is based on the PCA method instead of the EFA model (Cliff, 1988). Secondly, and most important, the number of factors retained according to this rule is proportional to the number of variables being analyzed (Ferrando & Anguiano-Carrasco, 2010). In practice, the use of this rule tends to grossly overestimate the number of factors that are truly meaningful and interpretable (Kline, 2014; Ruscio & Roche, 2012).

Another widely used method is Cattell's scree test (Cattell, 1966). The scree test is a graphical representation of the eigenvalues, and the factors to be retained are suggested by marked drops until the curve flattens out. Although this procedure is simple and can provide a useful complement to determine the number of factors, it involves subjective assessment, which may be problematic especially in cases where the plot does not offer an obvious solution – there is no clear drop point or "elbow" (Ledesma, Valero-Mora, & Macbeth, 2015). Thus, though a scree plot may provide an initial idea of the number of factors, it is necessary to complement the method with a less subjective alternative (Baglin, 2014).

Instead of using a single method to decide the number of factors, experts recommend that the decision be based on multiple criteria, a first set of which derives from the analysis of the residual correlations after extracting a determined number of factors (see Ferrando &

Anguiano-Carrasco, 2010). The rationale of this approach is that if the number of common factors is correctly estimated, the residual correlations between the variables after removing the factor influences should be close to zero. If nontrivial covariation remains unexplained, extracting more common factors could be attempted.

As stated above, if a statistical procedure is used to fit an EFA solution, rigorous assessments based on the magnitude of the residuals can be made as in any structural model (via goodness-of-fit test statistics and more descriptive indices derived from these statistics; see Ferrando & Lorenzo-Seva, 2017). A ~~L~~less formal recommendation~~s that can be used with~~ valid for any method (including PAF) ~~or that provide auxiliary information~~is for example ~~are now given. First is~~ visual inspection of the residual correlations~~,~~ and the root mean square of the residual correlations (RMSRC) as an overall summary index. However, ~~A~~although useful, ~~however,~~ th~~ese~~is ~~recommendation~~methods involve~~s~~ subjective assessment and ~~. S~~so~~,~~ a more rigorous ~~criterion~~ measure such as Kell~~e~~ey's criterion would be better~~an be used~~. ~~This~~ Kelley's criterion ~~is~~ simply ~~to~~ compares the RMSRC value ~~to~~ with the approximate standard error of a zero correlation (if residuals were negligible the compared values should be about the same).

Several ~~A~~auxiliary methods that have proven to be efficient and are recommended by experts can be used to ~~that~~ complement those based on residual analyses~~,which and are recommended by the experts, are~~: Horn's Parallel Analysis (Horn, 1965), Velicer's Minimum Average Partial test (Velicer, 1976), and the Hull method (Timmerman, Lorenzo-Seva, & Ceulemans, 2018). Among these methods, Parallel Analysis is the only one reported in a small fraction of the analyzed studies (4.6%). PA can be viewed as a refinement of the scree - test in which the subjectivity of the ~~letter~~ latter method is avoided. The basic idea is to determine the point of intersection between~~at which~~ the empirical scree curve and a simulated scree curve based on random data~~ intersect~~. PA has been found to generally perform well for identifying the correct number of factors under different situations (Hayton, Allen, & Scarpello, 2004; Peres-Neto, Jackson, & Somers, 2005; Lim & Jahng, 2019) and is therefore recommended.

Lastly, it is also important to use criteria related to the strength and interpretability of the factor-solution under scrutiny (e.g. h-index, determinacy index, and percentage of explained common variance; see Ferrando & Lorenzo-Seva, 2018). ~~As a~~Briefly~~ summar~~,~~ y,~~ these indices quantify the extent to which an EFA solution is strong and replicable regardless of the degree of statistical goodness of model-data fit. In effect, there is little sense in retaining a "weak", poorly-defined factor that is unlikely to generalize further, even if this factor is considered to be statistically significant. ~~We further note that t~~S~~hese properties of s~~trength and replicability mostly depend on the quality of the items: large commonalities and ~~so,~~thus a small amount~~s~~ of measurement error~~, which in turn~~ means that the percentage of common variance explained by the fitted solution (or the particular factor under scrutiny) will be high (see Ferrando & Lorenzo-Seva, 2018).

Overall, in applying EFA one seeks an optimal solution that is plausible for the data, parsimonious, strong and replicable, and theoretically interpretable, such that the decision regarding the number of factors should be based on an integrated and comprehensive analysis of the factor solution (Henson & Roberts, 2006; Lloret-Segura et al., 2014, 2017; Lorenzo-Seva et al., 2011). Our findings suggest that these recommendations regarding EFA are far from being heeded in transportation research. The least recommended procedure (i.e. Kaiser's rule) is the one most used by researchers, and in very few cases is its use well founded. It is also worth noting that 24% of the studies did not report on how the number-of-factors decision was taken.

2.6. Transformation (rotation) methods

In cases where more than one factor is retained, the direct solution is usually not interpretable after initial extraction, and must be rotated in order to transform the original factor solution into one that is mathematically equivalent but simpler and interpretable (Yaremko, Harari, Harrison, & Lynn, 1986). The term rotation derives from the fact that these transformations were originally performed graphically using geometrical representations (see Thurstone, 1938). Overall, rotation methods can be classified into two broad categories: orthogonal and oblique. In the orthogonal rotation factors are restricted to being uncorrelated, whereas in the oblique rotation they are allowed to correlate. Traditionally, researchers have used orthogonal rotations based on the assumption that they provide simpler factor structures that are more easily interpretable (e.g., Nunnally, 1978). In particular, the most commonly used method is Varimax, most likely because it is the default option in many statistical software applications (Baglin, 2014). However, this argument is flawed and in most cases unrealistic: in transportation and the social sciences, variables are usually interconnected and consequently some degree of relationship between the factors is to be expected (Gaskin & Happell, 2013). In this case, oblique rotations do not incorrectly constrain the inter-factor correlations to ~~be~~ zero but rather freely estimate them, which makes them the appropriate choice. Furthermore, when factors are non-trivially related, orthogonal rotations do not produce simpler solutions. (Fabrigar, Wegener, MacCallum, & Strahan, 1999). For these reasons, oblique rotations are to be favoured unless there is a strong argument supporting the utilization of an orthogonal rotation (Beavers et al., 2013).

In short, the choice of the rotation procedure must be guided by theory and expectations. If theory suggests that the factors are related, then an oblique rotation should be chosen. Since most EFA applications in transportation research deal with multiple dimensions of a general construct that are expected to be correlated with one another, oblique rotation should in principle be applied. In the absence of this information (i.e. a blind, purely exploratory study), our advice is to use Browne's (2001) recommendation of performing an oblique rotation as default. If the rotated solution suggests minor or negligible inter-factor correlations (say < .30), then an orthogonal solution can be specified in a second step (Lloret-Segura et al., 2014). Researchers should avoid the widespread practice of applying default orthogonal rotations because, if the factors are truly correlated, results will be biased (but not the reverse; see Fabrigar & Wegener, 2012).

A plethora of specific rotation procedures exist within each of the categories so far discussed (for a comprehensive review, see Browne 2001; Sass & Schmitt, 2010). However, the choice of a particular rotation procedure is generally of far less consequence than the overall choice of orthogonal or oblique rotation, as specific procedures tend to perform comparably well (Fabrigar et al., 1999; Sass & Schmitt, 2010). Thus, Varimax (Kaiser, 1958) for example is a good choice when the factors are expected to be uncorrelated. If factors are expected to be correlated, the popular Oblimin (Clarkson & Jennrich, 1988), Promax (Hendrickson & White, 1964) or Promin (Lorenzo-Seva, 1999) methods are good choices. Researchers should in all instances justify their choice of rotation criterion.

The rotation methods used in transportation studies are summarized in Table 4. Almost half of the studies applied orthogonal rotation (mainly Varimax), but the rationale for this choice is not provided, nor was the correlation between factors usually reported. Notably, in the few cases where correlations were reported, the factors are strongly correlated but do not appear to influence the type of rotation selected. A significant number of studies (24.8%) did not provide information on this point.

2.7. Reporting EFA results

In addition to clearly stating the procedures followed and decisions taken, it is also important to clearly report the EFA's results. The pattern loading matrix is perhaps the most obvious and important EFA output to be reported. In an orthogonal solution, pattern coefficients can be interpreted both as standardized regression coefficients (i.e. Beta weights), and as factor-variable correlations. They therefore indicate both the strength and direction of the relationship between the observed variables and the common factors and are crucial in interpreting factor solutions. Surprisingly, we identified few cases (31%) reporting the full pattern loading matrix.

Although it is recommended that researchers report the full pattern loading matrix, reporting only factor loadings above a certain value (usually |.30| or |.40|) remains a common practice. We found that 45% of the revised studies edited the matrix in this fashion, suppressing values under |.30| or |.40| in most cases. This practice is based on proposed criteria to determine "salient" loadings and to subsequently assign variables to factors (Costello & Osborne, 2005; MacCallumet al., 1999; Williams, Brown, & Onsman, 2010). It is highly recommended that the full matrix be reported because it provides a complete picture of the solution (Norris & Lecavalier, 2010). For example, it allows for a better inspection of variables with "cross-loadings" (i.e., variables with salient loading on more than one factor), which is something that researchers attempt to avoid, or at least minimize. The presence of cross-loadings in a variable suggests that this variable simultaneously measures more than one factor. A "complex" variable of this type does not contribute to clearly and univocally define the factors. Howard (2016) suggests retaining variables that "(a) load onto their primary factor above 0.40, (b) load onto alternative factors below 0.30, and (c) demonstrate a difference of 0.20 between their primary and alternative factor loadings" (p. 55). There is no agreement on the specific values proposed by the author, but the general approach is still useful.

In summary, although there are no strict rules as regards cross-loading and minimum acceptable values for factor-loadings, in the interests of improving reporting transparency it is preferable to report the full pattern loading matrix rather than just loading values above a given cut-off value. In this way other researchers can evaluate whether an alternative cut-off gives a different result or whether the loading matrix lends itself to different interpretations (Norris & Lecavalier, 2010). As mentioned, few of the revised articles reported the full matrix, and even worse, 24% of them failed to provide any table at all showing the factor-loadings. It should be highlighted that under-reporting this information hinders not only the correct interpretation of the EFA results but also their reproducibility/replicability.

With~~hen researchers use~~ oblique rotations, the pattern loadings ~~do not~~no longer ~~are~~ represent simultaneously standardized regression coefficients and correlations, ~~and variable-factors correlations. Rather, the elements of the pattern loading matrix~~but -are ~~solely~~ merely standardized regression coefficients. T~~wh~~he variable-factor~~s~~ correlations in this case are the elements of a different matrix known as a “structure coefficient matrix”. Pattern loadings and structure coefficients tend to be similar in the case of small inter-factor correlations and the higher the correlation, the greater the discrepancy. Researchers often refer to both types of coefficients as "factor loadings," making it difficult to know which type of coefficient they are referring to (Thompson, xxx). Reporting both matrices is therefore recommended for a more accurate interpretation of oblique factor solutions (Henson & Roberts, 2006; Thompson, 2004). In the case of an oblique solution, the estimated inter-factor correlation matrix should always be reported.

3. Discussion

The present article critically examines current practices in using EFA in transportation studies. Overall, the findings suggest that: (1) researchers fail to provide sufficient information to be able to adequately assess the appropriateness and quality of both the input data and the reported output; (2) methods used for extraction, retention and rotation are frequently unreported, and even those studies which do provide this information did not follow current recommendations; and (3) researchers do not offer clear justifications for the decisions made when applying EFA. In particular, the Little Jiffy approach (i.e., PCA, Kaiser's rule, and orthogonal Varimax rotation) remains widely used despite recommendations to the contrary. The pervasive use of these methods is in line with previous literature reviews (e.g., Fabrigar et al., 1999; Frías-Navarro & Pascual-Soler, 2012; Henson & Roberts, 2006; Howard, 2016; Norris & Lecavalier, 2010). The Little Jiffy approach is the default option in most used statistical software (Lloret-Segura et al., 2017), which seems to strongly influence how the EFA is applied. However, researchers should be aware that default options are not necessarily the best options and may lead to incorrect results when applied indiscriminately.

The reporting of EFA findings is routinely poor: basic information regarding whether the reported factor loading matrix is the pattern matrix or the structure matrix is omitted and in many cases a factor loading matrix is not even provided. This is worrisome since there is no guarantee of the validity of the results and replication becomes difficult. It is essential that studies provide the full loading matrix along with information regarding the software used, the type of correlation matrix analyzed, the factor extraction method, the criteria used for choosing the number of factors, the rotation method and the information supporting each decision, all of which serve to increase transparency in communicating EFA findings (Izquierdo et al., 2014).

The findings of the present study reveal a need to improve the application of EFA in transportation research. A joint effort by authors and reviewers will be necessary to promote best practices in this regard. Authors are encouraged to update their knowledge on EFA and to provide detailed information on the procedures used, justifying the choices made at each stage of an EFA application. Reviewers should examine applications of EFA more critically and where appropriate request more information on methods used, decisions taken and results. It is also important to strengthen data sharing in transportation research to facilitate the replicability of the results. Moreover, dissemination of practical guidelines on how to use, report and review applications of EFA would also be useful. A proposal of this type for authors and reviewers is presented in Table 5. We hope that this work helps to bridge the gap between recommended and reported EFA practices in transportation research.

Basic information and preliminary checks	Does EFA fit the research aims and the questions addressed? Is there any other more suitable approach (e.g. Confirmatory Factor Analysis)? Are the variables and data type clearly described? Is the sample size reasonable for conducting EFA? Are descriptive statistics (measures of central tendency, variability, distribution, and discrimination) for the variables reported? Is the type of correlation matrix (Pearson, Polychoric or Tetrachoric correlations) reported? Is it in line with the data type? Are sampling adequacy indices (e.g. KMO, Barlett's test) presented? Are their values adequate for EFA (e.g., KMO above 0.70)? Is the statistical software used stated?
Extraction method	Is the extraction method (ML, PAF, etc.) mentioned and justified? Is Principal Components Analysis (PCA) used instead of other superior methods? Is there a well-founded reason for this choice?
Factor retention	Are the factors retained theoretically well justified and supported by multiple criteria? Is the decision based on a comprehensive analysis of the factor solution? Is Kaiser's eigenvalues-greater-than-one rule avoided as a main criterion for factor retention? Or are other superior methods applied? (e.g. parallel analysis, MAP, analysis of residual correlations, model fit indices) Are there potential issues of underestimation (selecting too few factors) or overestimation (selecting too many factors)?
Factor Rotation	Is a rotation method used? Is the type of rotation method reported and justified? Is an oblique procedure selected as the first choice? Is the rotation method in line with the expected correlation between factors? Do the results include the correlations between factors?
Pattern loading matrix	Is the full pattern loading matrix reported? If an oblique rotation is used, is it clear what type of matrix is being reported (structure matrix, pattern matrix or both)? Do the variables load on their primary factor? Are there cross-loading issues (variables loadings on multiple factors)? How are the items with substantial cross-loadings handled? Does the factor-loading table include complementary information about the EFA (e.g., percentage of explained variance by each factor, extraction and rotation methods, type of correlation matrix, etc.)?

Table 5. Guiding questions for reporting Exploratory Factor Analysis.

Two caveats are worth mentioning. First, although the present study focuses on EFA methods used in transportation studies, Confirmatory Factor Analysis (CFA) is also a widely used statistical approach in the field and therefore a similar examination of its application would be valuable. Second, we provide some guidelines regarding good practices in EFA. However, the application of sound EFA methods can never compensate for limitations in primary data quality. In some cases we observed methodological weaknesses that significantly undermined the quality of the data used. Hence, studies examining prior decisions affecting the quality of the primary data (sampling strategy, selection/construction of instruments, data collection strategy, etc.) are also important.

Lastly, it is important to keep in mind that the proposed guidelines are by no means definitive. EFA procedures and approaches are continually evolving and authors should therefore make sure they are both aware of updates to well-established methods and alert to alternative and emerging approaches. Thus, t~~ start with, t~~his review has only dealt with analytical rotations. However, alternative solutions obtained by target or bifactor rotations (see Ferrando & Lorenzo-Seva, 2017) ~~can~~ are clearly ~~be~~ of ~~clear~~ interest in transportation research. More generally, new FA developments appear to verge~~seem to orient~~ towards "hybrid" forms of modeling that combine the flexibility of EFA with some of the advantages of CFA~~ advantages~~. For example, Bayesian FA allows an essentially CFA solution to be obtained in which certain cross-~~-~~loadings and correlated residuals are not constrained to ~~be~~ zero but estimated using informative "priors" based on researcher~~'~~s' knowledge. Exploratory structural equation modeling (ESEM) allows a flexible EFA solution to be embedded into a full structural model, among other things allowing~~, among other things, to test~~ measurement invariance to be tested across groups or relations between factors and external variables to be estimated~~ing~~ directly, ~~the relations between factors and external variables~~ without~~ no~~ needing to regress these variables on factor score estimates. Marsh, Morin, Parker and Kaur

~~et al.~~ (2014) provide a good overview of these new developments, ~~that~~ which ~~are~~ have already proven~~already~~ ~~feasible~~ viable and ~~that~~ will hopefully find their way into future transportation~~ing~~ applications.

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