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Evaluation of Exploratory Factor Analysis Performance for Survey with Predetermined Constructs

Nazim Aimran[1]*, Nurul Raudhah Zulkifli[2], Adzhar Rambli[1], Asyraf Afthanorhan[3], Adzmel Mahmud[4]

[1]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Malaysia, [2]Business School, Universiti Kuala Lumpur, 50250 Kuala Lumpur, Malaysia, [3]Faculty of Business and Management, Universiti Sultan Zainal Abidin, 21300 Kuala Nerus, Malaysia, [4]National Population and Family Development Board, 50350 Kuala Lumpur, Malaysia. *Corresponding Author's Email: ahmadnazim@uitm.edu.my

Abstract

The necessity of performing exploratory factor analysis (EFA) for predetermined constructs has been debated among researchers; some argue that performing EFA is essential before confirmatory factor analysis (CFA), and others contend that EFA is unnecessary when the items under construction have been predetermined. This study seeks to contribute to the ongoing discussion by examining whether it is necessary to perform EFA prior to conducting CFA when a theoretical model has already been established. To mimic the real-life scenarios, population data of size, n=500 with predetermined relationships between items and constructs was generated by using the Monte-Carlo Markov Chain method via the "MASS", "mvrnorm", and "psych" packages in R programming. The data generated for the population dataset were prespecified factor loadings for items under exogenous and endogenous constructs were set to 0.6 and 0.7, respectively. Next, samples of varying sizes (n=50, 100, and 300) were randomly selected from the generated population data. The results indicate that EFA yields unsatisfactory outcomes across all sample sizes (n=50, 100, and 300), as it failed to adequately discern items under predetermined constructs, as in the population dataset. Therefore, it is concluded that EFA is unsuitable for studies with predetermined constructs, especially when the sample size is less than 300.

Keywords: Confirmatory Factor Analysis, Exploratory Factor Analysis, Predetermined Model, Sample Survey.

Introduction

Exploratory factor analysis (EFA) refers to a group of multivariate statistical techniques aimed at identifying the smallest number of underlying constructs also known as dimensions, latent variables, synthetic variables, or internal attributes that can adequately account for the covariation among a set of items, which are also referred to as measured variables, observed variables, manifest variables, effect indicators, reflective indicators, or surface attributes (1–4). On the other hand, confirmatory factor analysis (CFA) is used to support the hypothesized factor structure (5), which enables researchers to validate or refute the underlying factor structures or dimensions identified in previous studies (6). The choice between EFA and CFA is often determined by a study's objectives and research context, a decision that has been debated among researchers. Some assert that performing EFA is necessary before CFA (7, 8), while a study contends that EFA is more appropriate in the early stages of scale development (9). Another perspective suggests that CFA is more suited for validating the factor structure if the study is more advanced and a prespecified theory or model is provided (10), and that sample size and data complexity should be considered when deciding between CFA and EFA (11). To add, CFA requires a larger sample size than EFA and is often employed when the data are more complicated and there are several variables to be examined (1, 12, 13). EFA and CFA have been extensively applied in psychology, marketing, and social sciences to explore new constructs and theories. Technically, EFA employed principal axis factoring as the extraction method. This method extracts factors from the original correlation matrix, with squared multiple correlation coefficients placed in the diagonal as initial estimates of the communalities (14). It is important to note that, often, principal component

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analysis (PCA) is mistaken for EFA. PCA and EFA have different purposes, in which PCA aims to reduce the number of items in the questionnaire to a smaller set and EFA is designed to measure a latent construct (6). On the other hand, CFA employs factor loading to validate the underlying items under constructs (15). A refined model evaluation was introduced, providing a more nuanced indices and criteria evaluation (16). In terms of model specifications, while EFA is a data-driven approach requiring no a priori assumption (17), CFA requires a strong empirical or conceptual foundation to specify and evaluate the model (13). Having discussed the differences between EFA and CFA, it is clear that EFA and CFA serve different purposes. Investigations into new psychological constructs and marketing strategies have been included in some of the recent studies using EFA (18), and the structure of the constructs for the developed questionnaire has been confirmed through CFA in several studies (19). However, there has been continuous debate on the need to perform EFA for predetermined constructs. If the model includes constructs that are not well tested in the literature (for the same country or industry) then EFA must be applied before CFA to check for the validity and reliability of the data (20). It was added that theories are not necessarily valid (i.e., they may not correctly identify respondents' bases for responding to individual items) (21). Therefore, EFA can give an initial clue as to factor structure, but only after ascertaining the actual number of factors represented by respondents' responses.

The statements were also supported, as it was pointed out that structural changes may occur due to cultural differences and item translation (1). Therefore, EFA provides a clear framework for defining the possible model that may arise. However, it is argued that performing EFA may lead to different model construction. For example, it was stated that the labour market construct consists of employment rate and wage rate, whereas the financial market construct consists of return on capital, investment rate, and national savings (22). If the relationship of investment rate is higher with the employment and wage rates, EFA will categorize the investment rate under the labour market construct. A review published in the field of educational sciences (23) examined 61 scale adaptation and development studies conducted in 2023. The findings revealed that studies which did not apply exploratory factor analysis (EFA) were generally adaptation studies. Given these varying perspectives, this study sought to investigate the suitability of performing EFA for predetermined constructs across different sample sizes.

Methodology

This study generated a population dataset of size n=500 using the Monte-Carlo Markov Chain method, implemented via the "MASS", "mvrnorm", and "psych" packages. The data generated for the population dataset were prespecified, with items' factor loadings for each exogenous construct were set to 0.6, and items' factor loading for the endogenous constructs were set to 0.7. The choice of factor loading to 0.6 as true indicator loadings was induced by the parameter value, which has been frequently noted as the minimum requirement for validating the measurement model under the CFA. Sample datasets of sizes n=50, 100, and 300 were taken from the population dataset to simulate a real-world scenario. The cases in each sample dataset were randomly selected using a pseudorandom number generator. The dataset consisted of four constructs: A, B, and C, serving as the exogenous constructs; and D as the endogenous construct. Each construct consisted of four items: A (X11, X12, X13, and X14), B (X21, X22, X23, and X24), C (X31, X32, X33, and X34), and D (Y11, Y12, Y13, and Y14). The sample size was based on the rule of 10, which recommends 10 samples for each indicator, and a more accurate method that requires at least 5 samples for each free parameter in the model, such as error terms and path coefficients (24). In addition, the constructs were predetermined based on established theoretical frameworks and prior literature (25, 26). The analysis involved six essential steps, beginning with data cleaning. We utilized the principal axis factor as the extraction method. The population dataset (n=500) was used as the benchmark for the sample datasets (n=50, 100, and 300). Through this measure, the biases of the EFA estimations in grouping the items could be observed. IBM SPSS Statistics version 21.0 was used for the analysis. Within the factor analysis function, the Varimax rotation method was selected. Varimax rotation is used in this study because the measured constructs are independent and do not influence each other. Normality assessment, reliability test, and multicollinearity were analyzed beforehand. Upon checking, all data were multivariate normal, and there were no multicollinearity issues in the dataset. To evaluate robustness and validity, EFA was conducted, followed by reliability testing using Cronbach's alpha values. The findings affirm that all Cronbach's alpha values were above 0.6, except for the value for construct B when n=50.

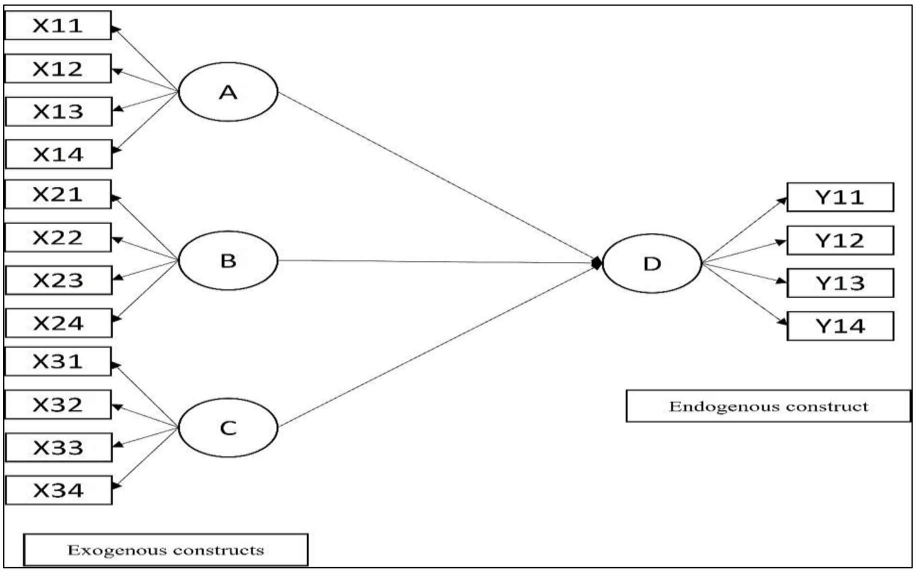

Figure 1: Theoretical Model

Exploratory Factor Analysis

Exploratory factor analysis (EFA) using the principal axis factoring method assumes that all variables within the first group and matrix are computed when the factor is removed (27). Consequently, factors were sequentially extracted until the correlation matrix accounted for a sufficiently large variance.

$$X = LF + \varepsilon \qquad [1]$$

$$\left[X_{i,1}\ X_{i,2}\ X_{i,3}\ \vdots\ X_{i,16}\right] = \left[L_{1,1} \cdots L_{1,4} \vdots \ddots \vdots L_{16,1} \cdots L_{16,4}\right]\left[F_1\ F_2\ F_3\ F_4\right] + \left[\varepsilon_1\ \varepsilon_2\ \varepsilon_3\ \vdots\ \varepsilon_{16}\right] \qquad [2]$$

Where X is the matrix of observed variables, L is the matrix of factor loading, F is the common factor and ε is the matrix of unique factors or error variation. It should be noted that L is the correlation between a variable and a factor, for example, $L_{1,2}$ represents the relationship between variable 1 and factor 2. The covariance matrix of X can be decomposed into:

$$\Sigma = L\Phi L' + \Psi \qquad [3]$$

Where Φ is the covariance matrix of the factors. It should be noted that factor loading is the estimation used in the CFA, by which the convergent validity is achieved if all items have factor loadings of 0.6 and above (28). However, In CFA, the structure of L is typically specified based on the theoretical model. The L is estimated by adjusting the discrepancy function, D to be minimum using the maximum likelihood (ML) estimator:

$$D_{ML} = log\ |\Sigma|\ + tr(S\Sigma^{-1}) - log|S| - p \qquad [4]$$

Where S represents the sample covariance matrix and p is the number of indicator variables in the model.

Fixed Number of Factor

In a factor analysis, a fixed number of factors refers to a predetermined or specified number of constructs. In this study, we specified the number of constructs and items to ensure that the output mimicked the predetermined theoretical model, as illustrated in Figure 1. This approach is often employed when the researcher is aware of the number of possible factors (or constructs) they perceive to be present in the dataset a priori. The fixed number of factors approach is a rather easyto-understand and direct way to determine the number of major components to be extracted. It is crucial to remember that this strategy could be susceptible to outliers in data collection. In this study, when EFA correctly classified items under their respective constructs (i.e., following the pre-determined model), it confirms that those dimensions are meaningful and distinct. This alignment between theoretical grouping and empirical factor structure is a strong sign that the identified factors represent real conceptual constructs.

Kaiser-Meyer-Olkin (KMO)

The suitability of the data for factor analysis was determined using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (3). The KMO measure represents the proportion of variance in the constructs that may be attributed to the underlying items. A high KMO value, approaching 1.0, suggests that factor analysis is suitable for the data. Conversely, if the value is less than 0.5, the results of the factor analysis may not be very useful (29). The KMO can be calculated as follows:

$$KMO = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} \hat{r}_{ij}^2} \qquad [5]$$

Where r_{ij} represents the correlation between variables i and j and $\hat{r}_{ij}$ represents the partial correlation between variables i and j.

Results

Table 1 shows that the KMO values for n=50, 100, 300 and 500 were above 0.5. Therefore, it can be concluded that all datasets were appropriate for the EFA procedure. Bartlett's test of Sphericity also showed the significance of the datasets used in this study. Therefore, there is substantial evidence to suggest a correlation between the variables. In addition, the KMO value increases as the sample size increases, suggesting that the minimum sample size required to perform EFA is 100 because KMO approaches 1.0 when n≥100.

Table 1: KMO Measure and Bartlett's Test for Sample 50, 100, 300 and 500

Sample Size	**50**	**100**	**300**	**500**
KMO Measure of Sampling Adequacy	0.664	0.806	0.859	0.878
Significance of Bartlett's Test of Sphericity	0.00	0.00	0.00	0.00

Table 2 shows the number of factors extracted for n=50, 100, 300, and 500, respectively. For this analysis, the number of factors was determined based on the Eigenvalue>0.9. The number of factors suggested varies, which are five factors when n=50 and n=100, and four factors when n=300 and n=500. These findings prove that EFA tends to suggest a different model from the predetermined theoretical model when the number of factors to be generated is not fixed. Therefore, researchers are expected to get different underlying items for each factor.

Table 2: Number of Factors Extracted by Sample Sizes

Sample Size	**Eigenvalue > 0.9**
50	5
100	5
300	4
500	4

For the next analysis, we fixed the number of factors to examine the estimation of EFA when the number of factors is fixed as in the theoretical model (Figure 1). Table 3 to Table 6 present the rotated factor matrix when n=50, 100, 300, and 500. The factor(s) were named A, B, C, and D if all the items under the construct(s) were correctly grouped. Conversely, we named the factors X1, X2, X3, and X4 if the items under the construct(s) were incorrectly grouped. Table 3 to Table 6 revealed that the item grouping pattern improved as the sample size increased. For example, the items under all constructs were incorrectly grouped when n=50. In contrast, the underlying items for construct D were grouped correctly when n=100.
In the case of n=300, the pattern of item grouping became better, with items under the two constructs (A and C) grouped correctly. Lastly, all items were grouped correctly when n=500.

Table 3: Rotated Factor Matrix for Sample n=50

Construct	X1	X2	X3	X4
X11	0.353			
X12		0.417		
X13	0.398			
X14	0.714			
X21				0.423
X22	0.508			
X23	0.697			
X24	0.367			
X31				0.647
X32			0.418	
X33			0.719	
X34			0.438	
Y11			-0.506	
Y12		0.635		
Y13			-0.515	
Y14		0.719		

Table 4: Rotated Factor Matrix for Sample n=100

Construct	X1	X2	X3	X4
X11	0.632			
X12	0.489			
X13	0.451			
X14	0.575			
X21			0.489	
X22	0.563			
X23	0.495			
X24	0.353			
X31			0.443	
X32		0.591		
X33		0.675		
X34			0.61	
Y11				0.636
Y12				0.574
Y13				0.739
Y14				0.575

Table 5: Rotated Factor Matrix for Sample n=300

Construct	X1	X2	X3	X4
X11	0.504			
X12	0.576			
X13	0.510			
X14	0.475			
X21				0.373
X22		0.382		
X23		0.641		
X24				0.341
X31			0.481	
X32			0.539	
X33			0.661	
X34			0.474	
Y11				0.613
Y12				0.588
Y13				0.747
Y14				0.541

Table 6: Rotated Factor Matrix for Sample n=500

Construct	X1	X2	X3	X4
X11	0.499			
X12	0.488			
X13	0.530			
X14	0.414			
X21		0.395		
X22		0.505		
X23		0.497		
X24		0.402		
X31			0.499	
X32			0.584	
X33			0.614	
X34			0.542	
Y11				0.632
Y12				0.612
Y13				0.675
Y14				0.551

Discussion

In this study, we extracted sample datasets of varying sizes (n=50, 100, and 300) from a population dataset of size, n=500. The selection of cases was random, in which all elements in the population dataset (n=500 cases) had an equal chance of being selected as the sample. This procedure was implemented to mimic the actual scenario in a real-life study. Thus, the results of this study might have differed if different samples were selected.

The predetermined factor loadings for the population dataset were set at 0.6 for all underlying items of the exogenous constructs (A, B, and C) and 0.7 for all underlying items of the endogenous construct, D. Therefore, the results may differ if different factor loadings were set in other studies (26). From this study, we affirmed that when employing the EFA method without fixing the number of factors, there is a tendency for the number of factors generated to differ from the theoretical model, especially when the sample size is small. When the number of factors is fixed and the sample size is sufficiently large (e.g., n≥300), we observed that the models closely mirrored the theoretical model. Essentially, n=300 ensures a more accurate representation of the underlying structure of the data through factor analysis. Larger sample sizes tend to yield more precise estimates of the factor loadings, leading to a more reliable representation of the relationship between variables, consistent with previous studies (15, 30).

However, it should be noted that the results generated were good as the sample size increased due to the high predetermined factor loading specified in the population dataset. If low factor loadings were prespecified, the results would not be as good even if the sample size is sufficiently large.

Based on the discussion, we believe that EFA is a good dimension-reduction technique when all the required criteria are met. However, in the case of predetermined constructs, researchers may use the CFA for modeling, without the need to perform the EFA. This aligns with the view that EFA provides greater flexibility in the early stages of research, particularly when the factor structure is uncertain, whereas CFA is more rigid and requires a predefined model structure (31). In real-life practice, specifically questionnaire-based research, all items under each factor must undergo a pretest and pilot test. This measure requires researchers to develop an individual content validity index (I-CVI) and scale content validity index (S-CVI), along with individual face validity index (I-FVI) and scale face validity index (S-FVI) (32). Therefore, we believe that the pre-test and pilot tests are sufficient to justify the model developed by the researchers.

Conclusion

EFA and CFA serve different purposes. EFA is suitable for studies with an exploratory nature (i.e., early-stage studies) because it can help in identifying the underlying constructs or reducing the model complexity. On the flip side, CFA is more suitable when the study is confirmatory (i.e., studies that use an established model). In this study, EFA was performed on datasets of varying sample sizes (n=50, 100, 300, and 500). The analysis revealed that the EFA was poor with small sample sizes. For example, when n=50 and 100, five factors were suggested instead of four and the underlying items were poorly categorized for all constructs. Since EFA is adaptive, it also tends to not perform well in categorizing items for larger sample sizes when the relationships between items are weak. Therefore, it is suggested that EFA be performed only when there is no theoretical model available for the study. However, it should be noted that a minimum sample size of at least 300 is necessary. In the case when a theoretical model is available, it is suggested that researchers do not perform EFA but straight away perform CFA for each construct of interest. To conclude, this study contributes to the field by informing survey design practices which can guide researchers in making informed methodological choices during the instrument development process.

Abbreviations

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Author Contributions

All authors contributed equally.

Conflict of Interest

The authors affirm the absence of any identified conflicts of interest associated with this publication and emphasize that there has been no considerable financial support for this work that might have affected its outcomes.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare no use of artificial intelligence (AI) for the write-up of the manuscript.

Ethics Approval

Not applicable.

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