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Comparison of Different Estimation Methods for Categorical and Ordinal Data in Confirmatory Factor Analysis*

Doğrulayıcı Faktör Analizinde Sınıflama ve Sıralama Düzeyindeki Veriler için Farklı Kestirim Yöntemlerinin Karşılaştırılması

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Abstract
In confirmatory factor analysis (CFA), which is used quite often for scale development and adaptation studies, the selected estimation method, affects the results obtained from the data. Because of the selected estimation method, the model parameters and their standard errors, and the model data fit values may alter the results substantially. So that, the purpose of this research is to compare the performance of different estimation methods for CFA. Maximum likelihood (ML), unweighted least squares (ULS) and diagonally weighted least squares (DWLS) are used in this research as estimation methods. These methods are applied in data sets and regression coefficients and their standard errors, t values, fit indexes and iteration numbers obtained from these estimation methods are examined. As a result, ULS method can converge with the minimum number iterations and it seems to be the more accurate method for estimating the parameters.

Keywords: Confirmatory factor analysis, weighted least square, unweighted least square, diagonally weighted least square

Öz
Ölçek geliştirme ve uyarlama çalışmalarında oldukça sık kullanılan doğrulayıcı faktör analizinde (DFA), hangi kestirim yönteminin kullanılması gerektiğine doğru karar vermek, çalışmadan elde edilen sonuçları etkilemektedir. Çünkü kullanılan kestirim yöntemi, model parametreleri ve onların standart hataları ve uyum indeksi değerleri gibi sonuçlar üzerinde etkiye sahiptir. Bu nedenle bu araştırmada, DFA'da kullanılan farklı kestirim yöntemlerinin performanslarını karşılaştırmak amaçlanmıştır. Araştırmada, maksimum olabilirlik maximum likelihood – ML), ağırlıklandırılmamış en küçük kareler (unweighted least square – ULS) ve diyagonal en küçük kareler (diagonally weighted least squares – DWLS) kestirim yöntemleri kullanılmıştır. Sınıflama ve sıralama düzeyinde olan veri setlerine bu kestirim yöntemleri uygulanmış ve bu kestirim yöntemlerinden elde edilen regresyon katsayıları ve bu katsayıların standart hatalar, t değerleri, uyum indeksleri ve tekrar sayıları incelenmiştir. Araştırma sonucunda ULS tekniğinin tüm veri setlerinde en az sayıda tekrar ile parametreleri tahmin ettiği ve ilgili örneklem verisine ait parametreleri tahmin etmek için en uygun teknik olduğu belirlenmiştir.

Anahtar Kelimeler: Doğrulayıcı faktör analizi, ağırlıklandırılmış en küçük kareler, ağırlıklandırılmamış en küçük kareler, diyagonal ağırlıklandırılmış en küçük kareler

INTRODUCTION

The social sciences and behavioral sciences rather focus on the latent variables that are not directly visible, and it is attempted to take decisions on latent variables through these variables. The Structural Equation Modelling (SEM) is widely used to identify the relationship between observable variables and latent variables (Jöreskog & Sörbom, 1996a; Sammel, Ryan & Legler, 1997). SEM is a set of statistical methods that allows describing the relationship between one or more continuous or

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categorical independent variables and one or more continuous or categorical dependent variables (Tabachnick & Fidell, 2007, p. 676). In other words, SEM is a comprehensive statistical approach for testing hypothese based on the relationship between observable variables and latent variables (Hoyle, 1995).

The Confirmatory Factor Analysis (CFA), a customized version of SEM, is often used for studies developing and adapting scales. Brown (2006) states that CFA can be used (1) to psychometrically evaluate measurements, (2) to validate the structure, (3) to test the effect of the method, and (4) to indicate invariance of test measurements. To perform a CFA on a data set, first a theory must exist or there must be a predetermined factor structure. Then, a model is created based on this information and the model is tested through the observed data set (Raykoy & Marcoulides, 2000, p. 95). In brief, the CFA model aims to assess whether data set supports the assumed relationship between a group of measured variables.

In social sciences, data are often collected by scoring multiple-choice items in two categories and ordinal items with three or more categories, but not by an equal-interval scale (Bandalos, 2014). Since there is a relationship of $a < b < c < d$ between ordinal variables in Likert scales and a relationship of $a < b$ between data that is scored in two categories, it is referred to as ordered categorical data while there is no order between coding in non-ordered categorical data (Cai, 2008). Bollen (1989) emphasizes that ordered categorical data are treated as continuous data due to technical limitations on measuring tools. However, this approach to categorical data would result in biased estimation of parameters and unfavourable standard errors (Babakus, Ferguson & Joreskog, 1997; DiStefano, 2002; Rigdon & Ferguson, 1991). And it is important to match between the assumptions underlying the statistical model and the empirical characteristics of the data to be analyzed (Flora & Curran, 2004).Therefore, different estimation methods have been developed according to the data structure.

Estimation Methods

A right decision on what estimation method to use for statistical analyses has a direct influence on results derived from a study. The most common estimation method in SEM is the maximum likelihood (ML) method because it is selected in default in many software packages. This method is capable to make consistent and unbiased estimations on properly defined models, large sample sizes, normally distributed independent, continuous and multivariate data sets (Kline, 2005). It was deduced in the literature that the use of ML as an estimation method particularly for non-normally distributed data sets with a few number of answer categories resulted in bias in factor loadings, standard errors, statistics for chi-square test, and goodness of fit indexes (Babakus et al., 1987; Bollen, 1989; Green, Akey, Fleming, Hershberger, & Marquis, 1997; Hutchinson & Olmos, 1998). However, ML would not give significantly biased results if the number of categories of ordered data is high, the size of the sample is large, and the observed items are almost distributed normally (Mîndrilă, 2010).

For ordered data, it is assumed that there is a continuous variable such as y_i^* under a variable measured sequentially, such as y_i, in factor analysis, and this continuous variable ranging from $-\infty$ to $+\infty$ indicates characteristics underlying responses at y_i^* order level (Forero, Maydeu-Olivares & Gallardo-Pujol, 2009; Jöreskog, 1990; Lee, Poon & Bentler, 1990; Muthén, 1984). Tetrachoric or polychoric correlations should be used in SEM when categorical and/or orded data are used to determine the underlying continuous latent variable (Muthén, 1984; Muthén & Kaplan, 1985). It is because a high level of bias occurs in the estimation of parameters, standard errors, and factor loads based on Pearson Product-Moment Correlation Coefficient (PCC) (DiStefano, 2002). So to solve this problem, Jöreskog and Sörbom (1996b) suggested that polychoric correlations as the most consistent and robust estimator. The bias of estimation of parameters, standard errors, and factor loads is reduced by using polychoric correlation instead of PCC matrix (Babakus et al., 1997; Rigdon &

Ferguson, 1991). While tetrachoric correlation is used for data with two categories, polychoric correlation is used for data with more than two categories.

Some of estimation methods developed for ordinal data are weighted least square (WLS), unweighted least square (ULS) and diagonally weighted least squares (DWLS). Babakus (1985) suggests using polychoric correlation for performing CFA on ordinal data instead of Pearson correlation. In all of these methods, asymptotic covariance matrix is used that is derived from polychoric correlation matrix estimated from the observed categorical variables (Katsikatsou, Moustaki, Yang-Wallentin, & Jöreskog, 2012). The weight matrix of ULS and DWLS is the diagonal form of asymptotic covariance matrix; and the weight matrix of WLS is the reverse of asymptotic covariance matrix. Only diagonal elements of asymptotic covariance matrix are used for DWLS (Yang-Wallentin, Jöreskog, & Luo, 2010).

WLS can be an alternative method for ordinal data in particular that is not distributed normally, highly skewed or kurtic, or both (Muthén, 1993). However, WLS estimation converges to asymptotic features very slowly, therefore its performance on a small sample size is not good (Katsikatsou et al., 2012). ULS, on the other hand, has some features such as lack of distributional assumption and ability to estimate all parameters at a time. But this method requires all observed variables to have a same level of scale (Kline, 2005; 159). Recently, the use of DWLS estimation method has become popular for factor analysis of ordinal data. This popularity is attributed to ability of using DWLS as a method to determine measurement invariance in case of using continuous variables and to ability of DWLS to estimate variances smaller than ULS can do (Forero et al., 2009).

Katsikatsou et al. (2012) point out that the DWLS and ULS estimation methods are more preferable than WLS and both of these methods display a similar performance in small sample sizes. Likewise, Yang-Wallentin et al. (2010) established in their simulation study that WLS performs poorly under symmetric and non- symmetric 2, 5 and 7 categories conditions compared to ULS, DWLS, and ML and ULS had a remarkable performance. Forero et al. (2009) compared ULS and DWLS methods in their simulation study. They found that ULS estimated parameters more accurately and displayed less variability as well as showing more accurate standard error values and better convergence. Mîndrilă (2010) compared estimation methods DWLS and ML. They found that ML estimated parameters more accurately in continuous and normally distributed data and DWLS estimated parameters more accurately in data sets not normally distributed. The literature has many studies that compared different estimation methods which have effects on results obtained (DiStefano, 2002; Forero et al, 2009; Hu, Bentler & Kano, 1992; Lei, 2009; Muthen & Kaplan, 1985; Rigdon & Ferguson, 1991; Yang-Wallentin et al., 2010). However, there are only limited number of studies performed on real data sets (Katsikatsou et al., 2012). So this study is focused on real data sets.

Taking a correct decision on what estimation method to use when performing a CFA as in all other statistical analyses influences the results obtained from the study because the estimation method used has an influence on model parameters and their standard error values and fit index. When performing a CFA, ML method is widely used which is utilized for continuous variables and assumes that observable variables have a multivariate normal distribution. However, most of variables used for social sciences and psychology are not continuous but categorical / ordinal (Yang-Wallentin et al., 2010), and it is not appropriate to use methods developed for continuous variables regardless of data structure for accuracy of results.

Purpose of the Study

The overall objective of this research was to compare performances of different estimation methods used for CFA. For this, the following research questions were addressed:

In ordinal set-1 and set-2, and categorical set-3,

1. What are regression coefficients obtained from ML, ULS and DWLS estimation methods and their standard errors?

2. What are t values obtained from ML, ULS and DWLS estimation methods?

3. What are fit indexes obtained from ML, ULS and DWLS estimation methods?

4. What is the number of iterations that ML, ULS and DWLS estimation methods do for convergence (achieving parameter estimation)?

METHOD

This is a theoretical research which compared different estimation methods for CFA:

Data Collection Tools

Ordinal variables used for this study were obtained from first and fourth year students of primary school teaching in 2007-2008 academic year at seven different universities in seven regions of Turkey using Epistemological Belief Scale. The total number of participants was 548. This instrument was developed by Schommer (1990), adapted by Deryakulu and Büyüköztürk (2002) and revised by Deryakulu and Büyüköztürk (2005). The scale was a three-factor scale including “Belief that Learning Depends on Effort” (17 items), “Belief that Learning Depends on Skills” (8 items) and “Belief that there is only one correct” (9 items), and 34 items in total. The respond category was a five-point Likert scale.

Beck Hopelessness Scale was used for categorical data set. The data set obtained by Dinler-İçöz (2014) from 200 children for their master thesis was used for this study with their permission. Beck Hopelessness Scale contains 20 items. Questions 1, 3, 5, 6, 8, 10, 12, 13, 15 and 19 have 1 point each for the response “no” and the questions 2, 4, 7, 9, 11, 14, 16, 17, 18 and 20 have 1 point each for the response “yes”. They are instructed to choose “correct” for statements they consider suitable, and “wrong” for statements they consider unsuitable. The score from the scale can vary from 0 to 20, and a high score indicates hopelessness whereas a low score indicates hope in children (Savaşır & Şahin, 1997).

Data Analysis

To compare sequential findings obtained from different sample sizes, two different data sets were created from a sample size of 548 persons as 250 (set-1) and 500 (set-2) randomly selected. Univariate and multivariate test of normality was performed on each data set. For this, first univariate normality assumption was tested for each item. West, Finch and Curran (1995) stated that if skewness value was greater than 2 and kurtosis value was greater than 7, they impaired univariate normality assumption of items. In the present study, the absolute value of skewness values for the data set of 250 persons ranged from 0.042 to 6.936, and kurtosis values ranged from 0.123 to 14.489. The skewness value of 26 items on the scale was greater than 2, the kurtosis value of 9 items was greater than 7, and all p values of chi-square values obtained had a significance level of 0.01 which was significant. For other data set, i.e., data set of 500 persons, the absolute value of skewness values ranged from 0.004 to 10.302 and kurtosis values ranged from 0.388 – 24.470. The skewness value of 28 items on the scale was greater than 2, kurtosis value of 2 items was greater than 7, and all p values of chi-square values obtained had a significance level of 0.001 which was significant. Based on these findings, not all of the items in both data sets displayed univariate normal distribution.

Mardia (1970) multivariate normality test results are listed in Table 1.

Table 1. The Findings of Multivariate Statistical Tests

Data Sets	Skewness			Kurtosis			Skewness and Kurtosis		
	Chi-square	Z score	p	Chi-square	Z score	p	Chi-square	Z score	p
Set-1	257,50	26,07	0,000	1375,94	14,15	0,000	879,71	0,000	257,50
Set-2	155,40	39,36	0,000	1417,09	22,32	0,000	2047,36	0,000	155,40

According to Table 1, two ordinal data sets in this study were determined that not multivariate normality.

The model must be identified or over identified to allow estimation of parameters in CFA (Brown, 2006; Kline, 2005). The model is referred to as unidentified if the number of unknown parameters is higher than available information in the model, as fully identified if the number of unknown parameters is equal to available information, and as over identified if the number of unknown parameters is less than available information (Brown, 2006). T-rule (Byrne, 1998) was used to identify the model. T-rule tests whether there is adequate degree of freedom to calculate and compare fit indexes, and there is adequate information for required estimation of parameters (Byrne, 1998).

Table 2. Model Identification with T Rules

Variable	Available Information	Estimation Information	Degree of Freedom
Ordinal (Set-1 and Set-2)	595*	71 Error: 34 Regression: 34 Covariance of latent variable: 3	524**
Categorical (Set-3)	210*	54 Error: 20 Regression: 34	156**

** v(v+1)/2 v: number of items*

*** degree of freedom, difference between available information and estimation information.*

According to Table 2, ordered and categorical data sets are over identified and so, CFA can be applied these data sets.

For categorical and ordinal data sets, unweighted least square and DWLS were used as estimation method in CFA. For this, an asymptotic covariance matrix was derived from all data sets. Regression values and their standard error values, t values and fit indexes were obtained and compared with this matrix. If the fit index values are $\chi2/df<3$, $0<RMSEA<0.05$, $0.97\leq NFI\leq 1$, $0.97\leq CFI\leq 1$, $0.95\leq GFI\leq 1$ and $0.95\leq AGFI\leq 1$, this indicates a perfect fit, if they are $4<\chi2/df<5$, $0,05<RMSEA<0.08$, $0.95\leq NFI\leq 0.97$, $0.95\leq CFI\leq 0.97$, $0.90\leq GFI\leq 0.95$ and $0.90\leq AGFI\leq 0.95$, this indicates an acceptable fit (Kline, 2005; Sümer, 2000). The method “weighted least squares" was excluded because there were non-positive elements in the asymptotic covariance matrix and a high sample size (≥1000) was not achieved in this study, which is necessary for this method to estimate parameters (Hoogland & Boomsma, 1998). In addition, parameters were estimated by maximum likelihood method even though data sets were not distributed normally.

FINDINGS

The regression coefficients and standard error values which obtained from ML, ULS and DWLS estimation methods are shown in Table 3 and Table 4.

Table 3. Regression Coefficients and Standard Error Values (Set-1 and Set-2)

Items	Set-1			Set-2		
	ML (SE)	ULS (SE)	DWLS (SE)	ML (SE)	ULS (SE)	DWLS (SE)
I1	0,72 (0,07)	0,67 (0,05)	0,67 (0,05)	142,29 (7,88)	0,73 (0,03)	0,74 (0,03)
I2	0,69 (0,06)	0,65 (0,05)	0,66 (0,05)	0,79 (0,04)	0,72 (0,03)	0,72 (0,03)
I3	1,09 (0,07)	0,83 (0,04)	0,83 (0,04)	1,10 (0,05)	0,86 (0,02)	0,86 (0,02)
I4	57,24 (5,82)	0,56 (0,07)	0,57 (0,07)	20,55 (1,36)	0,60 (0,04)	0,61 (0,04)
I5	36,33 (2,75)	0,72 (0,05)	0,73 (0,05)	74,51 (3,87)	0,74 (0,03)	0,74 (0,03)
I6	12,72 (1,37)	0,56 (0,06)	0,56 (0,07)	13,35 (1,00)	0,56 (0,05)	0,56 (0,05)
I7	0,66 (0,06)	0,59 (0,06)	0,60 (0,06)	0,63 (0,04)	0,62 (0,04)	0,62 (0,04)
I8	0,47 (0,06)	0,45 (0,06)	0,45 (0,06)	0,43 (0,04)	0,45 (0,05)	0,45 (0,05)
I9	23,62 (1,78)	0,73 (0,04)	0,73 (0,04)	28,05 (1,52)	0,71 (0,03)	0,72 (0,03)
I10	0,42 (0,06)	0,47 (0,07)	0,47 (0,07)	0,60 (0,06)	0,47 (0,05)	0,48 (0,05)
I11	74,38 (5,46)	0,75 (0,04)	0,75 (0,04)	73,32 (3,90)	0,73 (0,03)	0,74 (0,03)
I12	1,01 (0,06)	0,86 (0,03)	0,86 (0,03)	80,03 (3,74)	0,82 (0,03)	0,82 (0,03)
I13	0,60 (0,06)	0,60 (0,05)	0,61 (0,05)	0,63 (0,04)	0,62 (0,04)	0,63 (0,04)
I14	0,67 (0,06)	0,62 (0,06)	0,64 (0,06)	0,62 (0,04)	0,65 (0,04)	0,65 (0,04)
I15	25,64 (1,78)	0,78 (0,05)	0,78 (0,05)	15,55 (0,87)	0,72 (0,04)	0,72 (0,04)
I16	0,60 (0,07)	0,51 (0,06)	0,52 (0,06)	0,62 (0,06)	0,46 (0,04)	0,47 (0,04)
I17	21,89 (1,85)	0,68 (0,05)	0,69 (0,05)	24,24 (1,62)	0,63 (0,04)	0,63 (0,04)
I18	0,85 (0,17)	0,62 (0,09)	0,64 (0,09)	0,49 (0,09)	0,62 (0,08)	0,62 (0,07)
I19	0,52 (0,06)	0,56 (0,07)	0,56 (0,07)	1,03 (0,10)	0,44 (0,05)	0,45 (0,05)
I20	0,47 (0,05)	0,51 (0,07)	0,51 (0,07)	0,88 (0,06)	0,58 (0,05)	0,60 (0,05)
I21	0,41 (0,04)	0,54 (0,08)	0,55 (0,08)	0,81 (0,07)	0,31 (0,06)	0,35 (0,06)
I22	0,50 (0,05)	0,52 (0,08)	0,53 (0,08)	1,00 (0,06)	0,66 (0,05)	0,69 (0,05)
I23	0,40 (0,04)	0,45 (0,09)	0,46 (0,09)	0,76 (0,06)	0,48 (0,06)	0,51 (0,05)
I24	0,51 (0,06)	0,50 (0,07)	0,50 (0,07)	1,09 (0,08)	0,53 (0,06)	0,53 (0,05)
I25	0,46 (0,04)	0,65 (0,06)	0,66 (0,06)	0,72 (0,05)	0,61 (0,05)	0,61 (0,05)
I26	0,73 (0,19)	0,39 (0,06)	0,40 (0,07)	0,68 (0,12)	0,43 (0,07)	0,44 (0,09)
I27	0,71 (0,14)	0,41 (0,20)	0,43 (0,23)	0,66 (0,09)	0,39 (0,28)	0,38 (0,26)
I28	0,64 (0,08)	0,16 (0,18)	0,17 (0,22)	0,61 (0,05)	0,11 (0,22)	0,10 (0,20)
I29	1,05 (0,13)	0,02 (0,15)	0,02 (0,17)	0,88 (0,08)	0,06 (0,14)	0,07 (0,12)
I30	0,44 (0,07)	0,22 (0,19)	0,24 (0,20)	0,47 (0,05)	0,22 (0,24)	0,21 (0,22)
I31	1,11 (0,15)	0,25 (0,22)	0,27 (0,23)	0,94 (0,09)	0,29 (0,27)	0,28 (0,25)
I32	0,57 (0,09)	0,07 (0,12)	0,06 (0,15)	0,64 (0,07)	0,02 (0,16)	0,02 (0,15)
I33	0,77 (0,11)	0,40 (0,25)	0,42 (0,27)	0,82 (0,07)	0,40 (0,33)	0,39 (0,30)
I34	0,85 (0,12)	0,23 (0,20)	0,23 (0,21)	0,89 (0,08)	0,15 (0,21)	0,14 (0,19)

In Table 3, regression coefficient for set-1 ranged from 0.40 to 74.38 in estimations made by maximum likelihood (ML) and from 0.02 to 0.86 in estimations made by unweighted least squares (ULS) and diagonally weighted least squares (DWLS). More stable regression coefficients were achieved in methods ULS and DWLS. In evaluation of standard errors, standard error values varied between 0.04 and 5.82 in estimations made by ML; between 0.03 and 0.25 in ULS method, and between 0.03 and 0.27 in DWLS method. The mean of standard error values was 0.677 for ML, 0.090 for ULS and 0.096 for DWLS. The ULS method estimated parameters with least error for set-1. This finding is similar to that in the study by Forero et al. (2009).

Regression coefficient for set-2 ranged from 0.43 – 142.29 in estimations made by ML, from 0.02 to 0.86 in estimations made by ULS and DLWS. In evaluation of standard error values, standard error ranged between 0.04 and 7.88 in estimations made by ML, between 0.02 and 0.33 in ULS method, and between 0.03 and 0.30 in DWLS method. The mean of standard error values was 0.806 for ML, 0.089 for ULS and 0.084 for DWLS. The DWLS method estimated parameters with least error for set-2. This finding is similar to that in the study by Mîndrilă (2010).

It appears that similar regression coefficients and standard error values were obtained from ULS and DWLS methods. Katsikatsou et al. (2012) and Yang-Wallentin et al. (2010) found similar findings in their study. As sample size increased, similar findings were obtained in standard error values of parameter estimates from the ULS method whereas standard error values were lower in parameter estimates from DWLS. ULS and DWLS methods estimated parameters with less error as compared to the ML method.

Table 4. Regression Coefficients and Standard Error Values (Set-3)

Items	Set-3		
	ML (SE)	ULS (SE)	DWLS (SE)
I1	0,72 (0,10)	0,72 (0,08)	0,73 (0,07)
I2	0,57 (0,10)	0,57 (0,09)	0,57 (0,10)
I3	0,26 (0,11)	0,28 (0,12)	0,31 (0,12)
I4	0,38 (0,11)	0,38 (0,10)	0,38 (0,11)
I5	0,61 (0,10)	0,62 (0,08)	0,61 (0,08)
I6	0,89 (0,10)	0,88 (0,05)	0,90 (0,05)
I7	0,89 (0,10)	0,89 (0,05)	0,92 (0,05)
I8	0,49 (0,10)	0,48 (0,09)	0,49 (0,10)
I9	0,29 (0,05)	0,62 (0,09)	0,62 (0,10)
I10	0,37 (0,11)	0,36 (0,12)	0,38 (0,13)
I11	0,83 (0,10)	0,83 (0,06)	0,83 (0,06)
I12	0,52 (0,10)	0,51 (0,09)	0,54 (0,09)
I13	0,71 (0,10)	0,71 (0,07)	0,72 (0,08)
I14	0,72 (0,10)	0,72 (0,06)	0,75 (0,06)
I15	0,88 (0,10)	0,88 (0,05)	0,88 (0,06)
I16	0,52 (0,10)	0,53 (0,10)	0,55 (0,10)
I17	0,92 (0,09)	0,92 (0,04)	0,94 (0,04)
I18	0,87 (0,10)	0,87 (0,06)	0,87 (0,06)
I19	0,15 (0,03)	0,55 (0,20)	0,59 (0,13)
I20	0,57 (0,08)	0,69 (0,11)	0,70 (0,10)

In Table 4, regression coefficient for set-3 ranged from 0.15 to 0.92 in estimations mad by ML, from 0.28 to 0.92 in estimations made by ULS method, and from 0.31 to 0.94 in estimations made by DWLS. In evaluation of standard errors, standard error values were between 0.03 – 0.11 in estimations made by ML, between 0.05 and 0.20 in ULS method, and between 0.04 – 0.13 in DWLS method. The mean of standard error values was 0.094 for ML, 0.086 for ULS, and 0.085 for DWLS. The DWLS method estimated parameters with least error for set-3. Although similar regression coefficients were obtained from all parameter estimation methods, it appears that the ULS and DWLS methods estimated parameters with less error as compared to the ML method.

The t values which obtained from ML, ULS and DWLS estimation methods are shown in Table 5.

Table 5. t Values for Regression Coefficients

	Set-1			Set-2			Set-3		
Items	ML	ULS	DWLS	ML	ULS	DWLS	ML	ULS	DWLS
I1	10,29	13,40	13,40	18,06	24,33	24,67	7,20	9,00	10,43
I2	11,50	13,00	13,20	19,75	24,00	24,00	5,70	6,33	5,70
I3	15,57	20,75	20,75	22,00	43,00	43,00	2,36	2,33	2,58
I4	9,84	8,00	8,14	15,11	15,00	15,25	3,45	3,80	3,45
I5	13,21	14,40	14,60	19,25	24,67	24,67	6,10	7,75	7,63
I6	9,28	9,33	8,00	13,35	11,20	11,20	8,90	17,60	18,00
I7	11,00	9,83	10,00	15,75	15,50	15,50	8,90	17,80	18,40
I8	7,83	7,50	7,50	10,75	9,00	9,00	4,90	5,33	4,90
I9	13,27	18,25	18,25	18,45	23,67	24,00	5,80	6,89	6,20
I10	7,00	6,71	6,71	10,00	9,40	9,60	3,36	3,00	2,92
I11	13,62	18,75	18,75	18,80	24,33	24,67	8,30	13,83	13,83
I12	16,83	28,67	28,67	21,40	27,33	27,33	5,20	5,67	6,00
I13	10,00	12,00	12,20	15,75	15,50	15,75	7,10	10,14	9,00
I14	11,17	10,33	10,67	15,50	16,25	16,25	7,20	12,00	12,50
I15	14,40	15,60	15,60	17,87	18,00	18,00	8,80	17,60	14,67
I16	8,57	8,50	8,67	10,33	11,50	11,75	5,20	5,30	5,50
I17	11,83	13,60	13,80	14,96	15,75	15,75	10,22	23,00	23,50
I18	5,00	6,89	7,11	5,44	7,75	8,86	8,70	14,50	14,50
I19	8,67	8,00	8,00	10,30	8,80	9,00	5,00	2,75	4,54
I20	9,40	7,29	7,29	14,67	11,60	12,00	7,13	6,27	7,00
I21	10,25	6,75	6,88	11,57	5,17	5,83	-	-	-
I22	10,00	6,50	6,63	16,67	13,20	13,80	-	-	-
I23	10,00	5,00	5,11	12,67	8,00	10,20	-	-	-
I24	8,50	7,14	7,14	13,63	8,83	10,60	-	-	-
I25	11,50	10,83	11,00	14,40	12,20	12,20	-	-	-
I26	3,84	6,50	5,71	5,67	6,14	4,89	-	-	-
I27	5,07	2,05	1,87	7,33	1,39	1,46	-	-	-
I28	8,00	0,89	0,77	12,20	0,50	0,50	-	-	-
I29	8,08	0,13	0,12	11,00	0,43	0,58	-	-	-
I30	6,29	1,16	1,20	9,40	0,92	0,95	-	-	-
I31	7,40	1,14	1,17	10,44	1,07	1,12	-	-	-
I32	6,33	0,58	0,40	9,14	0,13	0,13	-	-	-
I33	7,00	1,60	1,56	11,71	1,21	1,30	-	-	-
I34	7,08	1,15	1,10	11,13	0,71	0,74	-	-	-

In evaluation of t values for regression coefficients, t values for set-1 ranged between 3.84 and 16.83 in estimations made by ML; between 0.13 and 28.67 in estimations made by ULS, and between 0.12 and 28.67 in estimations made by DWLS. The mean of these values was 9.64 for ML, 8.89 for ULS and 8.88 for DWLS. T values for set-2 ranged from 5.44 to 22.00 in estimations made by ML, from 0.43 to 43.00 in ULS method, and from 0.50 to 43.00 in estimations made by DWLS. The mean of these values was 13.66 for ML, 12.25 for ULS and 12.49 for DWLS.

For set-1 and set-2, higher t values were obtained in parameter estimations made by ML. Although standard error values were lower in estimations made by ULS and DWLS, the reason why estimations made by ML had a higher t value was to obtain very low regression values in estimations made by ULS and DWLS for several items.

For set-3, t values ranged between 2.36 and 10.22 in estimations made by ML, between 2.33 and 23.00 in estimations made by ULS method, and between 2.58 and 23.50 in estimations made by DWLS. The mean of these values was 6.48 for ML, 9.54 for ULS and 9.56 for DWLS. For set-3, higher t values were obtained in parameter estimations made by ULS and DWLS.

Fit indexes results which obtained from ML, ULS and DWLS estimation methods are shown in Table 6.

Table 6. Fit Index Values

		Set-1	Set-2	Set-3
ML	χ^2/df	2,91	4,32	1,04
	RMSEA	0,09	0,08	0,01
	CFI	0,88	0,91	1,00
	NFI	0,84	0,89	0,91
	GFI	0,74	0,79	0,92
	AGFI	0,70	0,76	0,90
ULS	χ^2/df	2,00	3,78	1,26
	RMSEA	0,06	0,08	0,04
	CFI	0,95	0,93	0,99
	NFI	0,90	0,91	0,97
	GFI	0,92	0,90	0,96
	AGFI	0,91	0,88	0,95
DWLS	χ^2/df	1,98	3,76	1,30
	RMSEA	0,06	0,07	0,04
	CFI	0,95	0,93	0,99
	NFI	0,90	0,91	0,97
	GFI	0,93	0,91	0,98
	AGFI	0,92	0,90	0,97

In evaluation of fit index values, for set-1 and set-2, by comparing with other methods, data sets are more fit to DWLS method. On the other hand, the fit indices were obtained by ULS method is higher than ML method. Fit index values were very similar to each other that were obtained from estimations made by ULS and DWLS. Katsikatsou et al. (2012) and Yang-Wallentin elt al (2010) obtained similar findings from their study. The model created with estimations made by ML fell below the acceptable level.

For set-3, estimations made by ML had higher match in fit indexes $\chi 2$/df and RMSEA, and estimations made by ULS and DWLS methods had higher match in fit indexes NFI, GFI and AGFI. Similar values were obtained from all three parameter methods in fit index CFI.

The iteration numbers of ML, ULS and DWLS estimation methods for convergence are shown in Table 7.

Table 7. Iteration Numbers

	Set-1	Set-2	Set-3
ML	28	20	8
ULS	20	18	5
DWLS	24	29	9

To have standard error values at an acceptable level, estimation of parameters continues iteratively. When iteration ends, this means that no significant changes will occur in estimations of parameters. If there is only few number of iterations, this means that relevant parameter estimation method better matches with the data set of sample. The reason is that different parameter estimation methods have different distributional assumptions (Marsh & Grayson, 1995). In evaluation of number of iterations, ULS method estimated parameters with the least number of iterations in all data sets. This finding was similar to that in the study by Forero et al. (2009). For set-1, ML method estimated parameters with the highest number of iterations, and for set-2 and set-3 DWLS method estimated parameters with the highest number of iterations. This finding shows that the estimation method which displayed optimum match with relevant data sets was ULS.

CONCLUSIONS and DISCUSSION

It is found that ULS and DWLS methods estimated parameters with less standard errors in ordinal data sets comparing to ML method. The ULS method yielded better results in lower sample sizes whereas DWLS method yielded better results in higher sample sizes. In estimation of parameters made by ULS and DWLS, fit values for the CFA model created were higher and values obtained were acceptable levels. Even in lower sample sizes, estimation made by ULS and DWLS methods achieved higher fit index values. The model crated with estimations made by ML method fell below an acceptable level. In ordinal data sets it is therefore revealed that fit index values for estimations made by ML method did not have adequate levels in univariate and multivariate Likert-type response patterns not normally distributed. As the size of the sample was increased, fit indexes were somewhat improved but fit indexes RMSE, CFI and GFI did not show the expected level. In estimations made by ULS and DWLS methods, as the size of sample was increased, fit index values were somewhat reduced, and all fit indexes had expected values except for AGFI obtained from estimations made by ULS for set-2.

In categorical data sets, it is found that the ULS and DWLS methods estimated parameters with less standard error as compared to the ML method; and the method which estimated parameters with the least error was DWLS. Since the fit index AGFI give fit values that are adjusted based on the degree of freedom for the model created by the number of variables when different models are applied to the same data set, it is more suitable value used to compare fit indexes obtained from all methods (Mîndrilă, 2010). The fit index AGFI was demonstrated to have a higher value in ULS and DWLS methods than that of ML method.

As provided in findings, the ULS method estimated parameters with the least number of iterations in all data sets, and it is the more accurate method to estimate parameters of relevant sample data.

In future research, the researches will examine the performance of WLS method with larger sample sizes (≥1000). And large number of categories can be used real data analyses for examine the ML method result. Because categorical methodology can outperform continuous methodology with more than five categories (Beauducel & Herzberg, 2006).

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GENİŞ ÖZET

Giriş

Ölçek geliştirme ve uyarlama çalışmalarında oldukça sık kullanılan doğrulayıcı faktör analizinde (DFA), hangi kestirim yönteminin kullanılması gerektiğine doğru karar vermek, çalışmadan elde edilen sonuçları etkilemektedir. Çünkü kullanılan kestirim yöntemi, model parametreleri ve onların standart hataları ve uyum indeksi değerleri gibi sonuçlar üzerinde etkiye sahiptir. DFA yaparken en çok sürekli değişkenler için kullanılan ve gözlenen değişkenlerin çok değişkenli normal dağılım gösterdiğini varsayan maksimum olabilirlik (maximum likelihood – ML) yöntemi kullanılmaktadır. Ancak sosyal bilimlerde ve psikolojide kullanılan değişkenlerin birçoğu sürekli değil sınıflama/sıralama düzeyindedir (Yang-Wallentin vd., 2010). Sıralama düzeyindeki veriler için geliştirilen kestirim yöntemlerinden bazıları ağırlıklandırılmış en küçük kareler (weighted least square – WLS), ağırlıklandırılmamış en küçük kareler (unweighted least square – ULS) ve diyagonal en küçük kareler (diagonally weighted least squares – DWLS) kestirim yöntemleridir. Bu üç yöntemde de gözlenen kategorik değişkenlerden kestirilen polikorik korelasyon matrisinden elde edilen asimptotik kovaryans matrisi kullanılmaktadır (Katsikatsou, Moustaki, Yang-Wallentin, & Jöreskog, 2012).

Bu araştırmanın genel amacı, DFA'da kullanılan farklı kestirim yöntemlerinin performanslarını karşılaştırmaktır. Bu amaçla çalışmada, aşağıdaki problemlere cevap aranmıştır.

Sıralama düzeyindeki birinci (set-1), ikinci (set-2) ve sınıflama düzeyindeki (set-3) veri setinde;

1. ML, ULS ve DWLS kestirim yöntemlerinden elde edilen regresyon katsayıları ve bu katsayıların standart hataları nasıldır?
2. ML, ULS ve DWLS kestirim yöntemlerinden elde edilen t değerleri nasıldır?
3. ML, ULS ve DWLS kestirim yöntemlerinden elde edilen uyum indeksleri nasıldır?
4. ML, ULS ve DWLS kestirim yöntemlerinin yakınsayabilmek (parametre kestirimlerine ulaşmak) için yaptıkları tekrar (iteration) sayıları nasıldır?

Yöntem

Doğrulayıcı faktör analizinde farklı kestirim tekniklerinin karşılaştırıldığı bu araştırma temel bir araştırma niteliğindedir.

Bu çalışmada kullanılan sıralama düzeyindeki veri setleri, 2007-2008 eğitim öğretim yılında Türkiye'nin yedi bölgesindeki yedi farklı üniversitede, birinci ve dördüncü sınıfta öğrenim gören sınıf öğretmenliği öğrencisine Epistemolojik İnanç Ölçeği'nin uygulanmasıyla elde edilmiştir. Sıralama düzeyinde farklı örneklem büyüklüklerinden elde edilen bulguları karşılaştırabilmek amacıyla 548 kişilik örneklem büyüklüğünden 250 (set-1) ve 500 (set-2) kişilik seçkisiz olarak seçilen iki farklı veri seti oluşturulmuştur. Sınıflama düzeyindeki veri seti için Beck Umutsuzluk Ölçeği kullanılmıştır. Dinler-İçöz'ün (2014) yüksek lisans tez çalışması için 200 çocuktan elde ettiği veri seti (set-3), izin alınarak bu çalışmada da kullanılmıştır. Bütün veri setleri için tek değişkenli ve çok değişkenli normallik testleri yapılmış olup, veri setlerinde yer alan tüm maddelerin tek ve çok değişkenli normal dağılım göstermediği belirlenmiştir.

Sonuçlar ve Tartışma

Sınıflama ve sıralama düzeyindeki veri setlerinden asimptotik kovaryans matrisi elde edilmiştir. Bu matrisler ile regresyon değerleri ve bu değerlere ait standart hata değerleri, t değerleri ile uyum indeksleri elde edilmiş ve karşılaştırılmıştır.

Set-1 için farklı kestirim teknikleriyle hesaplanan regresyon katsayılarına ait bulgulara göre ULS ve DLWS'nin ML'ye göre daha stabil sonuçlar verdiği belirlenmiştir (ML: 0,40 - 74,38; ULS ve DWLS: 0,02 – 0,86). Standart hata değerleri incelendiğinde ise, ML ile yapılan tahminlerde 0,04 - 5,82; ULS'de 0,03 – 0,25 ve DWLS'de 0,03 – 0,27 arasında standart hata değerleri elde edilmiştir. Standart hata değerlerinin ortalaması ML için 0,677; ULS için 0,090 ve DWLS için 0,096'dır. Set-1 için en az hata ile parametre tahminini ULS tekniği yapmaktadır. Bu bulgu, Forero vd.'nin (2009) çalışması ile benzerlik göstermektedir.

Set-2 için farklı kestirim teknikleriyle hesaplanan regresyon katsayıları incelendiğinde yine ULS ve DLWS'nin ML'ye göre daha stabil sonuçlar verdiği belirlenmiştir (ML: 0,43 - 142,29; ULS ve DLWS: 0,02 – 0,86). Standart hata değerleri incelendiğinde, ML ile yapılan tahminlerde 0,04 - 7,88; ULS'de 0,02 – 0,33 ve DLWS'de 0,03 – 0,30 arasında standart hata değerleri elde edilmiştir. Standart hata değerlerinin ortalaması, ML için 0,806; ULS için 0,089 ve DWLS için 0,084'dır. Set-2 için en az hata ile parametre tahminini DWLS tekniği yapmaktadır. Bu bulgu, Mîndrilă'nın (2010) çalışması ile benzerlik göstermektedir.

Set-3 için regresyon katsayılarının ML ile yapılan tahminlerde 0,15 - 0,92; ULS tekniğinde 0,28 – 0,92 ve DWLS ile yapılan tahminlerde 0,31 – 0,94 arasında değerler aldığı belirlenmiştir. Standart hata değerleri incelendiğinde, ML ile yapılan tahminlerde 0,03 - 0,11; ULS tekniğinde 0,05 – 0,20 ve DWLS tekniğinde 0,04 – 0,13 arasında standart hata değerleri elde edilmiştir. Standart hata değerlerinin ortalaması ML için 0,094; ULS için 0,09 ve DWLS için 0,09'dur. Set-3 için en az hata ile parametre tahminini DWLS tekniği yapmaktadır. Tüm parametre tahmin tekniklerinde benzer regresyon katsayıları elde edilmekle birlikte, ULS ve DWLS tekniklerinin ML tekniğine göre daha az hata ile parametre tahminleri yapabildiği belirlenmiştir.

Set-1 ve set-2 için ML ile parametre tahminlerinde daha yüksek t değerlerinin elde edildiği belirlenmiştir. Standart hata değerlerinin ULS ve DWLS tahminlerinde daha düşük olmasına karşın, ML tahminlerinin daha yüksek t değerine sahip olmasının nedeni, ULS ve DWLS tahminlerinde bazı maddeler için oldukça düşük regresyon değerlerinin elde edilmesidir. Set-3 için t değerlerinin ML ile yapılan tahminlerde 2,36 - 10,22; ULS tekniğinde 2,33 – 23,00 ve DWLS ile yapılan tahminlerde 2,58 – 23,50 arasında değerler aldığı belirlenmiştir. Bu değerlerin ortalaması, ML için 6,48; ULS için 9,54 ve DWLS için 9,56'dır. Set-3 için ULS ve DWLS ile parametre tahminlerinde daha yüksek t değerlerinin elde edildiği belirlenmiştir.

Set-1 ve set-2 için ULS ve DWLS tahminleri ile elde edilen uyum indeksi değerleri birbirine oldukça benzer olduğu, ML tahminlerinin ise örneklem büyüklüğündeki artış ile birlikte uyum indekslerinde bir miktar iyileşme olsa da RMSE, CFI ve GFI uyum indekslerinin beklenen düzeyi göstermediği belirlenmiştir. Set-3 için de ULS ve DWLS daha iyi sonuç vermiştir.

ML, ULS ve DWLS kestirim yöntemlerinin yakınsayabilmek (parametre kestirimlerine ulaşmak) için yaptıkları tekrar (iteration) sayıları incelendiğinde ise ULS tekniğinin tüm veri setlerinde en az sayıda tekrar ile parametreleri tahmin ettiği belirlenmiştir. Bu bulgu, Forero vd.'nin (2009) çalışması ile benzerlik göstermektedir. Set-1 için ML, set-2 ve set-3 için ise DWLS tekniğinin en fazla sayıda tekrar ile parametreleri tahmin ettiği görülmektedir. Bu bulgu, ilgili veri setleri ile en iyi uyumu gösteren tahmin tekniğinin ULS olduğunu göstermektedir.

Sonuç olarak ULS tekniğinin tüm veri setlerinde en az sayıda tekrar ile parametreleri tahmin ettiği ve ilgili örneklem verisine ait parametreleri tahmin etmek için en uygun teknik olduğu belirlenmiştir.