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Analyzing Factor Structure of The Scales By Hierarchical Clustering Analysis: An Alternative Approach

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Abstract: In this study, factor structure obtained by exploratory factor analysis, where principal components factor extraction technique of the "Epistemological Belief Questionnaire" was used, was compared to cluster constructs obtained by the agglomerative hierarchical clustering analysis. By using "Pearson Correlation" similarity criteria, it was discussed which construct obtained by "Complete Linkage" and "Ward's Linkage" methods was more concordant with exploratory factor analysis results. Research group of this study consisted of total 243 students who attended Ankara University, Faculty of Educational Sciences, Department of Preschool Teaching in 2006-2007 academic year. In the research group, 1-4 grade level students were included on a voluntary basis. As the cluster memberships obtained by Complete Linkage method were examined, it was determined that two items, unlike exploratory factor analysis, were replaced from the second cluster into the third. As the cluster memberships obtained by Ward's Linkage method were examined, it was seen that the construct obtained by the exploratory factor analysis was attained identically.

Key words: Construct Validity, Exploratory Factor Analysis, Cluster Analysis, Complete Linkage Method, Ward's Linkage Method

INTRODUCTION

One of the validity types frequently used in scale developing and adaptation in behavioral sciences is construct validity.

Generally speaking, construction is a pattern which consists of correlated specific components or correlations between components. In this context, construct validity process of a measurement tool is mainly based on analysis of correlations between answers to items included in a given tool. It is attempted to create evidence for construct validity to determine whether measurement tools measure a given construction or to what extent they measure. To this end, first construction to measure is defined and then measurability of the tool is examined (Atılgan, Doğan and Kan, 2007; Tekin, 2000).

Factor analysis is one of the frequently used techniques to obtain evidence for construct validity of measurement tools. It can be defined as multivariate statistics, which gathers wide range of correlated variables, and attempts to find out or discover a narrower range of conceptually significant variables (factors, dimensions). There are many techniques to determine factors in factor analysis. In other words, there are a lot of techniques in factor extraction. They could be grouped as classical factor extraction techniques and principal component analysis. Principal axes, maximum likelihood and multiple grouping techniques are some of the classical factor analysis techniques. Among these, principal axes approach is the most frequently used (Büyüköztürk, 2002; 2007).

Principal component analysis is another statistics frequently used as a factor extraction technique. Principal component analysis (PCA) produces components, whereas factor analysis (FA) generates factors. What makes principal component analysis different from classical factor analysis techniques is that error term in calculation of the common factor variance of variables in principal component analysis is disregarded, whereas error variance in FA defined as residual variance unexplained by common factors in the model is taken into account. It might be suggested that all factor extraction techniques are used in an attempt to determine factors which considerably contribute to variance of a data set or components. To this end, an approach on a basis of multiplexing or minimizing variance is used. One of the reasons why PCA is commonly used in behavioral sciences relates explained general factor in scales (Büyüköztürk, 2002; 2007).

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Cluster analysis is a comprehensive (general) term which associates many classification processes. These processes come from groups or clusters empirically generated by the method. More clearly, clustering method is a multivariate statistical method which starts with data sets including information about a sample of units and enables us to reorganize the units in relatively similar/homogenous groups (Aldenderfer and Blashfield, 1984).

Cluster analysis rather groups individuals or objects more similar than others according to the defined features in a cluster. Thus, in-cluster homogeneities and cross-cluster heterogeneities are maximized. If the applied clustering is accomplished, objects in the cluster in geometrical drawings are nearest, but objects in different groups are farthest from one another (Hair and *et al*., 2006). Cluster analysis reduces data by clustering all observations according to the defined criteria by the researcher or produces upper groups.

Main aim of cluster analysis is to reveal similarities between units according to certain features and classify them under categories based on these similarities. When compared to factor analysis, cluster analysis attempts to group objects, and factor analysis attempts to group variables. The latter could be considered as a statistical method which groups variables under sub-groups. Here, variables in the same cluster are mutually high correlated, but variables in different sub-clusters are relatively non-correlated. In other words, grouping in factor analysis is based on changes in variables (variance-covariance), while it is based on proximity in cluster analysis (Hair and *et al*., 2006).

In the literature, many algorithms are suggested for cluster analysis. However, it is possible to bring the clustering methods generally under two basic algorithms as "hierarchical clustering methods" and "nonhierarchical methods".

Hierarchical clustering methods are particularly appropriate for smaller (typically $n<250$) samples. Researchers need to decide how to define similarity or dissimilarity and how to agglomerate or discriminate clusters in hierarchical clustering analysis (Everitt, Landau and Leese, 2001; Hair and *et al*., 2006). Hierarchical clustering methods are divided into two as divisive and agglomerative methods. In the beginning, all observations are accepted as a single cluster in divisive hierarchical clustering method. Afterwards, the number of clusters is reduced one, and proximity matrix is restored, and according to similarity or dissimilarity criterion similar units are placed into the n cluster, thus n unit is gradually placed into a single cluster respectively 1, 2, 3…(n-r)…..(n-3), (n-2), (n-1) (Everitt, 1980). In agglomerative hierarchical clustering method, each observation or unit forms a cluster in the beginning. In other words, the process starts with an n number of individuals and an n number of clusters. Then, the number of clusters is reduced one and proximity matrix is restored, and according to similarity or dissimilarity criterion, n unit is gradually placed into a single cluster respectively n, (n-1), (n-2),...(n-r),...3,2,1 (Everitt, 1971). In other words, the process continues reducing the number of clusters at each stage and finally agglomerates all units in a single large cluster.

In the agglomerative hierarchical clustering method, various approaches (clustering algorithms) in unit agglomeration are applied. Among these, the following are most commonly used (Anderberg, 1973; Everitt and Dunn, 2001; Hair and *et al*., 2006; Şentürk, 1995; Yaylalı, Oktay, Akan, 2007): Single Linkage/Nearest Neighborhood Method; Complete Linkage Method/Farthest Neighborhood Method; Average Linkage Method; Ward's Linkage Method and Centroid Linkage Method. The present study explains only "Complete Linkage Method/Farthest Neighborhood Method" and "Ward's Linkage Method", since these two are used.

Complete Linkage Method:

In this method which is similar to Single Linkage Clustering, clustering approach is based on maximum distance. The method, also known as Farthest Neighborhood, starts with assigning the farthest two points to a cluster and, as a similar reason, ends with linking clusters with other clusters. The farthest distance is the criterion in point-cluster linkage or cluster-cluster linkage. Distance between two clusters corresponds to the farthest distance between a point in the first cluster and a second one in the second cluster (Aldenderfer and Blasfield, 1984, Hair and *et al*., 2006; Milligan, Martha and Cooper, 1985). Complete Linkage technique does not guarantee a sound production of all clusters, when the distance between observations in the same cluster is lower than a certain value (Tatlıdil, 1992).

Ward's Linkage Clustering Method:

Unlike other clustering methods which calculate distances between clusters, Ward's Linkage method, also known as Smallest Variance, minimizes in-cluster error sum of squares, and produces clusters which maximize homogeneity. Smallest clusters with lowest error sum of squares from each stage are linked to create clusters with minimum in-cluster homogeneity and cross-cluster heterogeneity (Çelik, Satıcı and Çelik, 2005; Hair and *et al*., 2006; Tatlıdil, 1992).

Clustering is based on similarity or dissimilarity of units. Therefore, the first step of the analysis is similarity or dissimilarity matrix production. When all variables are measured at the same scale level (for example, a question of group attitude), data standardization is mostly inessential. When variables are measured at different scale levels, it is an important issue. The most frequently used way of standardization is transforming each variable to standard scores (Z scores) (Hair and *et al*., 2006). Moreover, in the literature, it is shown that cluster analysis has different performances for continuous and discontinuous types of variables. In a study, Kayri (2007) suggest cluster analysis (by two stage cluster analysis method) cluster continuous variables better, based on Akaike's Information Criterion and Bayesian Information Criterion. In the light of this suggestion, it must be considered that cluster analysis might be affected by variable structures in data set.

Purpose:

Main aim of this study is to compare factor structure obtained by exploratory factor analysis, where principal components factor extraction technique of the "Epistemological Belief Questionnaire" was used and the constructs obtained in the agglomerative hierarchical clustering analysis by using "Complete Linkage-Farthest Neighborhood" and "Ward's Linkage-Smallest Variance" methods. In this context, it was attempted to determine which construct discovered by two different cluster analyses was more concordant with the exploratory factor analysis results.

With the above mentioned purpose in mind, this study is considered important because it serves to extend use of cluster analysis to applied social sciences such as education and psychology and it might be used as a additional findings production method related to the construct validity, particularly in measurement tool development and adaptation process.

MATERIALS AND METHOD

Research Model and Group:

The research focuses on the comparison of exploratory factor analysis results used in determining the factor structure of psychological measurement tools and the hierarchical clustering analysis results where two different methods are used. Therefore, this study is a basic research, and basic researches are the studies producing theoretical information.

In cluster analysis, "Pearson Correlation" is used as a similarity criterion in "Complete Linkage Method/Farthest Neighborhood" and "Ward's Linkage-Smallest Variance" methods. According to Özdamar (2004), this method is eligible for determining dissimilarity between variables rather than units/individuals. Pearson correlation is based on Pearson's Momentums Multiplication at a metric level. In unit or individual clustering versus variable cluster, researchers transpose normal data table which consists of variables in columns and individuals/units in rows. Thus, correlation is found between individuals by using columns as individuals and rows as variables and the correlations build cells of similarity matrix (Garson, 2009).

Research group of this study consisted of total 243 students who attended Ankara University, Faculty of Educational Sciences, and Department of Preschool Teaching in 2006-2007 academic year. In the research group, 1-4 grade level students were included on a voluntary basis.

Data Gathering Tool:

To provide an example of cluster analysis, the study attempts to compare factor structure obtained by exploratory factor analysis of "Epistemological Belief Questionnaire" and the constructs obtained in the agglomerative hierarchical clustering analysis and to examine which construct obtained by linkage and similarity criterion is more concordant with exploratory factor analysis results. As a result, first factor structure obtained in the adaptation studies of the given tool is briefly defined and then factor analysis results of the study are presented.

Epistemological Belief Questionnaire (EBQ) was developed by Schommer in 1990 to measure the individuals' beliefs of knowledge and learning. EBQ, which was adapted into the Turkish culture by Deryakulu and Büyüköztürk (2002), consists of three factors that are "Beliefs about Effort-Based Learning, Beliefs about Ability-Based Learning, and Belief about the Single Truth". In this research, the 34-item form of EBS, which was obtained by the second study by Deryakulu and Büyüköztürk in 2005, was used.

EBQ was adapted into the Turkish culture by Deryakulu and Büyüköztürk (2002) and reliability and validity study was performed over a group of 595 Turkish university students. The original scale is in English and has a four-factor structure. In the first study, it was concluded that the scale had a three-factor structure in the Turkish culture. The first factor was called "Beliefs about Effort-Based Learning (18 items), the second was called "Beliefs about Ability-Based Learning" (9 items), and the third was called "Belief about the Single Truth" (8 items). Cronbach Alpha internal consistency coefficients calculated for scale scores were .83 for the first factor, .62 for the second factor and .59 for the third factor. In the second study, conducted by Deryakulu and Büyüköztürk in 2005 with a group of 626 university students, an item with low item-total correlation in the second factor of the first study was removed from the scale. Furthermore, it was observed that an item in the first factor loaded in the second factor. It was also seen that the three-factor structure of the scale was maintained. Moreover, fit statistics as a result of confirmatory factor analysis were found as GFI=0.89, AGFI=0.87, RMS=0.09 (standardized RMS=0.07), RMSEA=0.05. It was stated that the three-factor structure of EBQ was an eligible, valid model. Cronbach Alpha internal consistency coefficients were found as .84 for the first factor, .69 for the second factor and .64 for the third factor. In this research, the 34-item form of EBS, obtained by the second study in 2005, was used.

RESULTS AND DISCUSSIONS

In this section, first exploratory factor analysis results of Epistemological Belief Questionnaire are presented and then cluster analysis findings obtained by "Complete Linkage Method/Farthest Neighborhood" and "Ward's Linkage" methods are given. Cluster analysis is limited to three clusters, as factor structure of Epistemological Belief Questionnaire was found as three in both adaptation study and the present study.

As presented in Table 1, in exploratory factor analysis of Epistemological Belief Questionnaire over a different group within the framework of this research, item 10 ("Being a good student mostly requires memorizing"), was removed from the scale, as it showed high factor loadings in more than one factor. Item 25 ("Average school students are an average success in their after-school life") was removed from the scale, as it had a factor loading below .30. There are 18 items in "Beliefs about Effort-Based Learning", the first factor in this case, 7 items in "Beliefs about Ability-Based Learning" and 8 items in "Belief about the Single Truth".

Table 1: Exploratory factor analysis results of epistemological belief questionnaire

Factor 1: Beliefs about Effort-Based Learning Items	Rotated Factor Loading	Factor 2: Beliefs about Ability- Based Learning Items	Rotated Factor Loading	Factor 3:Belief about the Single Truth Items	Rotated g Factor Loadin
1	.55	19	.56	27	.42
2	.43	20	.66	28	.46
3	.66	21	.67	29	.57
4	.39	22	.55	30	.57
5	.65	23	.69	31	.54
6	.41	24	.44	32	.53
7	.49	26	.32	33	.56
8	.46			34	.52
9	.61				
11	.63				
12	.70				
13	.43				
14	.56				
15	.57				
16	.48				
17	.60				
18	.41				
Explained Variance = % 16.185		Explained Variance= % 8.581		Explained Variance = % 8.558	
Cronbach-Alpha= .83		Cronbach-Alpha= .68		Cronbach-Alpha= .67	
KMO=.77				Bartlett's Test of	
Sphericity: χ^2 (sd=496)= 1906.270, p=.00					

A. Cluster Analysis Findings obtained by Complete Linkage (Farthest Neighborhood)

In Table 2, linkage results obtained by Complete Linkage Method (Farthest Neighborhood) are presented.

Table 2: Linkage results obtained by complete linkage (farthest neighborhood) method

	Cluster Combined			Stage Cluster First Appears		Next Stage
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	
1	12	13	.570	0	0	25
2	3	11	.492	0	0	3
3	3	5	.466	2	0	10
4	29	30	.425	0	0	20
5	15	16	.397	0	0	18
6	8	10	.396	0	0	19

Table 2: Continue

7	19	20	.385	0	0	14
8	1	9	.382	0	0	15
9	21	22	.377	0	0	21
10	3	14	.336	3	0	18
11	25	26	.333	0	0	27
12	27	32	.318	0	0	22
13	6	7	.270	0	0	24
14	18	19	.261	0	7	21
15	1	2	.246	8	0	24
16	28	31	.233	0	0	20
17	23	24	.224	0	0	22
18	3	15	.222	10	5	23
19	8	17	.215	6	0	23
20	28	29	.204	16	4	27
21	18	21	.172	14	9	30
22	23	27	.158	17	12	29
23	3	8	.151	18	19	26
24	1	6	.127	15	13	28
25	4	12	.121	0	1	26
26	3	4	.058	23	25	28
27	25	28	.045	11	20	29
28	1	3	.013	24	26	31
29	23	25	.010	22	27	30
30	18	23	-.064	21	29	31
31	1	18	-.240	28	30	0

When Table 2 is examined, it is seen that the first row shows the first stage of cluster analysis and it has 31 clusters. Under the "Cluster Combined" heading, the 12th variable (item) in Cluster 1 and the 13th variable (item) in Cluster 2 are the farthest observations. The next column, "Coefficents", measures distance between observations and the farthest distance in the sample appears as .570. "Stage Cluster First Appears" column shows at what stage a cluster is shaped. "Next Stage" column shows at what stage an observation in that row becomes a cluster after linkage with another observation. For instance, in the first row, it is seen that the 12 and the 13th variables are the farthest variables and these two variables will create the first cluster, including the fourth variable (item) at the 25th stage.

As a result of linkage presented in Table 2, cluster memberships in Table 3 appear. Accordingly, when cluster memberships obtained by Complete Linkage Method (Farthest Neighborhood) method are examined, it is clear that the 18 variables (items) in the first cluster are the same as the first factor obtained by exploratory factor analysis. When memberships of the second cluster are examined, it is seen that, unlike exploratory factor analysis, item 24 and item 26 shifts to the third cluster, and there are 5 items in this cluster. It is also clear that the number of items in the third cluster increases from 8 to 10, when these two items shift to the third cluster.

Table 3: Cluster memberships obtained by complete linkage (farthest neighborhood) method

Variable (Item)	Cluster	Variable (Item)	Cluster
1	1	19	2
2	1	20	2
3	1	21	2
4	1	22	2
5	1	23	2
6	1	24	3
7	1	26	3
8	1	27	3
9	1	28	3
10	1	29	3
11	1	30	3
12	1	31	3
13	1	32	3
14	1	33	3
15	1	34	3
16	1		
17	1		
18	1		

B. Cluster Analysis Findings obtained by Ward's Linkage (Smallest Variance) Method

In Table 4, linkage results obtained by Ward's Linkage (Smallest Variance) Method (Farthest Neighborhood) are presented.

As it is clear from Table 4, the first row shows the first stage of cluster analysis and it consists of 31 clusters. When the "Clusters Combined" column is examined, it is clear that the 12th variable (item) in Cluster 1 and the 13th variable (item) in Cluster 2 are the nearest observations and the distance between these two variables is .285. It is seen that the 12th and the 13th variables in the first row will create the first cluster, including the first variable (item) at the 29th stage.

Table 4: Linkage results obtained by ward's linkage (smallest variance) method

	Cluster Combined			Stage Cluster First Appears		Next Stage
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	
1	12	13	.285	0	0	29
2	3	11	.531	0	0	3
3	3	5	.764	2	0	12
4	29	30	.976	0	0	24
5	15	16	1.174	0	0	20
6	8	10	1.372	0	0	19
7	19	20	1.565	0	0	18
8	1	9	1.756	0	0	15
9	21	22	1.944	0	0	14
10	25	26	2.111	0	0	27
11	27	32	2.270	0	0	21
12	3	14	2.413	3	0	22
13	6	7	2.548	0	0	20
14	18	21	2.679	0	9	18
15	1	2	2.804	8	0	22
16	28	31	2.921	0	0	21
17	23	24	3.033	0	0	26
18	18	19	3.121	14	7	26
19	8	17	3.202	6	0	23
20	6	15	3.274	13	5	25
21	27	28	3.344	11	16	24
22	1	3	3.413	15	12	28
23	4	8	3.459	0	19	25
24	27	29	3.483	21	4	27
25	4	6	3.487	23	20	28
26	18	23	3.490	18	17	30
27	25	27	3.448	10	24	30
28	1	4	3.391	22	25	29
29	1	12	3.308	28	1	31
30	18	25	2.954	26	27	31
31	1	18	1.740	29	30	0

As a result of the observed linkage in Table 4, cluster memberships presented in Table 5 appear.

Table 5: Cluster memberships obtained by ward's linkage-smallest variance method

Variable (Item)	Cluster	Variable (Item)	Cluster
1	1	19	2
2	1	20	2
3	1	21	2
4	1	22	2
5	1	23	2
6	1	24	2
7	1	26	2
8	1	27	3
9	1	28	3
10	1	29	3
11	1	30	3
12	1	31	3
13	1	32	3
14	1	33	3
15	1	34	3
16	1		
17	1		
18	1		

As the cluster memberships in Table 5 obtained by Ward's Linkage (Smallest Variance) method were examined, it was seen that the structure was identical with the structure in the exploratory factor analysis. In other words, in exploratory factor analysis, the 18 items under the first factor generated the first cluster in cluster analysis, the 7 items under the second factor generated the second cluster in cluster analysis and the 8 items under the third factor generated the third cluster in cluster analysis.

As the cluster memberships obtained by Ward's Linkage (Smallest Variance) method were examined, it was seen that the structure in the first cluster was identical with the structure in the exploratory factor analysis.

Main aim of this study is to compare factor structure obtained by exploratory factor analysis, where principal components factor extraction technique of a measurement tool was used and the constructs obtained in the agglomerative hierarchical clustering analysis by using "Complete Linkage-Farthest Neighborhood" and "Ward's Linkage-Smallest Variance" methods.

Eventually, it can be considered that the agglomerative hierarchical clustering analysis applied by Ward's Linkage Method may be used as an alternative approach in producing additional findings related to the construct validity of scales. Moreover, as a similar reason, it can be suggested that the usage of other linkage methods such as Single Linkage Clustering (Nearest Neighborhood Method), Average Linkage Method, and Centroid Linkage Method and other similarity and dissimilarity criterion may be tested if they are eligible in producing construct validity findings.

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