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Comparison of Results Obtained from Hierarchical Cluster Analysis Methods and Different Distance-Similarity Measures in Determining the Factor Structures of Scales

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Abstract

The general purpose of this study is to compare the results obtained by using different distance and similarity measures in hierarchical cluster methods that can be used to reveal the factor structures of the scales. The anxiety scale developed by Büyüköztürk (1997) and applied to 954 university students studying at Muş Alparslan University in 2012 was used within the scope of the research. SPSS and Lisrel package programs were used in the analysis of the data. As a result of the analyzes, the methods that give the best factor structure in Hierarchical cluster methods used within the scope of the research are the Average linkage and the Ward method. When the calculated distance and similarity measures are compared, the cluster results obtained by using Euclidean, Squared Euclidean, Minkowski, Manhattan City Block, Pearson, and Cosine methods are similar in all Hierarchical methods in general. However, it was concluded that the measures that gave the best factor structure in all methods used within the scope of the research were Pearson and Cosine similarity measures. When researchers perform cluster analysis on any educational continuous data, it will be practical in terms of time and effort to first prefer the Pearson and Cosine method and the Average linkage and Ward's method in hierarchical clustering methods, to obtain the best result.

Keywords: Distance and similarity measurements, Exploratory factor analysis, Hierarchical clustering analysis, Scale development

INTRODUCTION

Problem State

Many features measured in the social and educational sciences cannot be directly observed. Especially, it is an important problem for researchers to measure the psychological characteristics of attitude, perception, anxiety, etc. that cannot be directly observed with the least error and to reveal the existing implicit structures. The vast majority of psychological traits are latent traits that cannot be directly observed, and they can only be measured by observing individuals' behavior or behavioral predispositions. Scales and inventories are generally used to measure such psychological structures (Erkuş, 2012). Measurement tools that measure psychological structures reliable and valid way require a rigorous process. Researchers obtain evidence for validity in all processes, from the development of a test to its implementation, scoring, and interpretation. An important problem for researchers is to

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increase the quality of this valid evidence. Exploratory and Confirmatory Factor Analysis methods are generally used for construct validity in scale development processes (Çokluk, Güçlü, and Büyüköztürk, 2010). However, these methods have some limitations such as not being able to use them when the number of individuals is low (n>150), being ineffective in testing homogeneity, and calculating factor models according to the level of correlation (Bollmann, Hölzl, Heene, Küchenhoff & Bühner, 2015). Researchers may not reach a high sample size in all cases. In addition, it requires the assumption of homogeneity as well as the assumption of normality in the application of test statistics. The inability of individuals or variables to come from a single universe is very important in determining the statistical method to be preferred. For these reasons, the suspicion that the variables included in the data set cannot come from a single universe constitutes the beginning of the cluster analysis (Kayri, 2007). In cases where different characters are in the universe, the descriptive statistics to be obtained for the universe or the parameter estimates to be made for this universe may be deviating (Duncan, Susan, Strycker, & Okut, 2002).

Another method that can be used to explore the factor structures of the scales is the Hierarchical Cluster Analysis method (Tay-Lim, 1999). In these methods, the measures calculated according to many distances and similarity measures are clustered with different Hierarchical clustering algorithms. The starting point of most statistical operations, such as cluster analysis, factor analysis, and multidimensional scaling, is distance or proximity matrices obtained from variables that include the states of pairs. Clusters, factors, structures, and dimensions are defined based on these criteria (Tombak, 1996).

Cluster Analysis

Cluster analysis aims to divide the data set into homogeneous subgroups. Thus, researchers can access more detailed information for each subset created (Kayri, 2007). The general purpose of this technique is to classify ungrouped data according to their similarities or differences and to help the researcher obtain appropriate, useful, and summarizing information (Harrigan, 1985). Cluster analysis functions for four different purposes. These include;

- It is to divide n units (individuals, cases), objects into subgroups as homogeneous and heterogeneous as possible according to their properties.
- To divide p number of variables into subsets that are supposed to explain common features according to the determined values and to reveal common factor structures.
- By considering both units and variables together, it is possible to divide the common n unit into sub-sets with common characteristics according to the variable p.
- To reveal the biological and typological classification that is thought to be formed naturally or possibly in the population through the structures determined according to the p variable (Özdamar, 2013).

Cluster analysis is a solution process consisting of several steps. Data entry is the first stage of analysis. Then, the distance matrix of the objects is obtained with an appropriate distance or similarity measure showing the distances, similarities, or differences of the data or variables with each other (Bryan, 1994; Koldere-Akin, 2008). Many different criteria are used continuously in similarity and distance measurements. These differ according to the type of the measured variable and the level of measurement. Similarity criteria give the proximity value between two objects, while similarity criteria give the distance value between two objects. The large similarity value shows that the two objects are very different from each other, and the small similarity value shows that these two objects are very close to each other (Tombak, 1996). The distance and similarity measures used in the study are summarized in Table 1 (Anderberg, 1973; Everit, 1974; Tatlıdil, 1996; Tombak, 1996; Günay-Atbaş, 2008; Ergüt, 2011).

Table 1. *Distance and similarity measures*

Method	Distance/ Similarity	Formula	Features
Euclidean	Distance measure	$d_{ij} = \left[\sum_{k=1}^{p}(x_{ik} - x_{jk})^2\right]^{1/2}$	Euclidean distance is the most commonly used distance measure. It is simply the geometric distance in multidimensional space.
Squared Euclidean	Distance measure	$d_{ij}{}^2 = \sum_{k=1}^{p}(x_{ik} - x_{jk})^2$	Squared Euclidean distance is the square of the Euclidean distance criterion. If there is no relationship between the variables, it is recommended to prefer the Euclidean and Squared Euclidean methods.
Minkowski	Distance measure	$d_{ij} = \left[\sum_{k=1}^{p}\lvert x_{ik} - x_{jk}\rvert^{\lambda}\right]^{1/\lambda}$ λ	It is a general distance measure. Euclid and Manhattan distance measurements are a special form of Minkowski distance measurement.
Manhattan City Block	Distance measure	$d_{ij} = \sum_{k=1}^{p}\lvert x_{ik} - x_{jk}\rvert$	This is the special case of Minkowski distance for λ=1. This distance is based on the sum of the absolute value of the differences.
Chebyshev	Distance measure	$d_{ij} = \max\left(\lvert x_{ik} - x_{jk}\rvert\right)$	This distance measure is defined as the maximum of the absolute values of the differences. Minkowski is a special case of distance
Pearson	Similarity measure	$r_{ij} = \frac{\sum_{k=1}^{p}(x_{ik} - \bar{x}_{i.})(x_{jk} -}{[\sum_{k=1}^{p}(x_{ik} - \bar{x}_{i.})^2 \sum_{k=1}^{p}(x_{jk}}$	It is a widely used similarity measure for variables measured at the ordinal and ratio level.
Cosine	Similarity measure	$s_{ij} = \cos\alpha = \frac{x_i' x_j}{\lVert x_i\rVert \lVert x_j\rVert} = \frac{\sum_{k=}^{p}}{[(\sum_{k=1}^{p} x_{ik}^2)}$	The similarities between units are determined by taking the cosine of the angle between two vectors.

Cluster Analysis Methods

The step to be taken after determining the similarity or distance criterion to be used in the clustering analysis studies is to select the appropriate clustering technique. Many algorithms have been proposed for this. However, in the literature, these algorithms are generally grouped under two headings. These are Hierarchical Cluster Analysis Methods and Non-hierarchical Cluster Analysis Methods. In both techniques, the common goal is to maximize the differences between the clusters and the similarities within the clusters (Koldere-Akin, 2008). Whether the researcher decides which technique to use depends on whether or not prior knowledge of the number of clusters is known. If the number of clusters is known, Non-Hierarchical methods (K-Means, Medoids, Hill Climbing, fuzzy, etc.) are preferred, while if the cluster number is not known, Hierarchical cluster methods (Complete Linkage, Single Linkage, Average Linkage, Ward's, Median, Centroid, etc.) are preferred (Özdamar, 2013). The methods of staged (hierarchical) cluster analysis used within the scope of the research are summarized in Table 2.

Table 2. *Hierarchical cluster analysis methods*

Method	Alternative Name	Generally Used	Description of the Distance Between Clusters
Single Linkage	Nearest neighbor	Similarity or distance matrix	The minimum distance between object pairs, one in a cluster, one in another cluster
Complete Linkage	Furthest Neighborhood	Similarity or distance matrix	Maximum distance between object pairs, one in a cluster, one in another cluster
Average Linkage	UPGMA	Similarity or distance matrix	Average distance between object pairs, one in a cluster, one in another cluster
Centroid	UPGMC	Distance (data matrix required)	It is the Squared Euclidean distance between the average vectors (centroid).
Median	WPGMC	Distance (data matrix required)	It is the square Euclidean distance between the weighted centers (centroid).
Ward's	Minimum Sum of Squares.	Distance (data matrix required)	After merging, it is the sum of the increase in the sum of squares within the clusters for all variables.

U: Unweighted; W: Weighted; PG: Group pair; A: Average; C: Center (Everit, Landau & Leese, 2001).

In many studies conducted in the literature, the results of different Hierarchical clustering analysis methods were compared using different distance and similarity measures (Edelbrock, 1979; Milligan, 1981; Tonbak, 1996; Tay-Lim, 1999; Koldere-Akin, 2008; Ergüt, 2011; Dinler, 2014). Studies on cluster analysis are often used in the fields of business, finance, computer, statistics, etc., but studies in the fields of Social and Educational Sciences are limited. In particular, studies comparing the results including the comparison of different distance and proximity measures, which can be used to reveal the factor structures of the scales measuring the psychological dimension, are limited and generally obtained through simulation data. In this respect, it is thought that this research will contribute to the literature.

The general purpose of this study is to compare the results obtained by using different distance and similarity measures in hierarchical clustering methods that can be used to reveal the factor structures of the scales. In line with this general purpose, answers to the following questions were sought. In determining the factor structures of the scales;

- How does the use of different Hierarchical cluster methods affect the factor structures obtained?

- How does the use of different distance and similarity measures affect the results of hierarchical clustering?

- How do the factor structures obtain from hierarchical cluster methods and the factor structures obtained by EFA change?

METHOD

This study is a descriptive study in that it aims to compare the results obtained by using different distance and similarity measures in hierarchical clustering methods used to reveal the factor structures of the scales. The study group of the research consists of 954 university students studying at the Faculty of Education of Muş Alparslan University in the spring semester of the 2012-2013 academic year.

Data Collection Tool

The anxiety scale towards the research developed by Büyüköztürk (1997) was used to determine the anxiety of university students within the scope of this research. The Anxiety Scale for Research consists of a single factor and 12 items. The total explained variance in the anxiety scale was obtained as 41.9%, and the item factor loadings varied between 0.54 and 0.73 (Büyüköztürk, 1997).

Data Analysis

Within the scope of the research, the measurements obtained from the Research-Oriented Anxiety Scale were analyzed using SPSS and Lisrel statistical package programs. First, the scores obtained from all scale items were converted into standard scores (Z) and the extreme values were deleted. To reveal the factor structure of the scale, the distance/similarities of the items of the scales were calculated by using seven different distance-similarity measures (Euclidean, Squared Euclidean, Minkowski, Manhattan City Block, Chebyshev, Pearson, Cosine) and these coefficients were clustered by using six different (Average Linkage, Single Linkage, Complete Linkage, Median, Cendroid, Ward's) Hierarchical Cluster techniques. The number of clusters (factors) was decided by examining the dendrograms obtained as a result of hierarchical clustering. The fit statistics (RMSEA, CFI, NNFI, and AGFI) obtained by using different distance/similarity measures and performing Confirmatory Factor Analysis on the items clustered by different Hierarchical cluster techniques were compared. In line with another purpose of the study, the factor structure of the scale was obtained by Exploratory Factor Analysis and compared with the factor structures obtained by Hierarchical Clustering methods. In addition to the statistical method and technical knowledge to be applied, scale development requires a good level of knowledge and infrastructure related to the theory to be measured. However, this research focused only on the scores obtained from the scale items, and the results were limited to the comparison of the statistical methods and techniques used.

FINDINGS

Different Hierarchical cluster techniques used according to different distance/similarity methods used within the scope of the research were calculated to examine the factor structure of the Research-Oriented Anxiety Scale. The results of the cluster analysis conducted to determine the factor structure of the anxiety scale are given in Tables 3, 4, 5, 6, 7, 8, and 9.

Table 3. *Euclidean distance measure*

	Factor-1	Factor-2	χ^2/df	RMSEA	CFI	NNFI	AGFI
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.092	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Nearest Neighbor	1.5.6.7.9.10.12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Furthest Neighbor	1.5.6.7.9.10.12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Centroid	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Median	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Ward's	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93

According to the findings in Table 3, the cluster analysis method obtained using the Euclidean distance and the EFA results are generally similar. The fit values obtained from all other methods within the scope of the study are similar (χ^2/df = 1.78; RMSEA = 0.042; CFI = 0.96; NNFI= 0.95) except for the median and centroid methods (χ^2/df = 5.47; RMSEA = 0.10; CFI= 0.79; NNFI= 0.74).

Table 4. *Squared euclidean distance measure*

	Factor-1	Factor-2	χ^2/df	RMSEA	CFI	NNFI	AGFI
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.092	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Nearest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93
Farthest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93

Centroid	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Median	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Ward's	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.042	0.96	0.95	0.93

According to the findings in Table 4, the cluster analysis method obtained using the Squared Euclidean distance and the EFA results are generally similar (χ^2/df =1.78; RMSEA=0.042; CFI=0.96; NNFI=0.95). The worst fit values were obtained from the median and centroid methods (χ^2/df =5.47; RMSEA = 0.10; CFI = 0.79; NNFI=0.74). In Figure 2, the Dendrogram of the clustering analysis results made according to Ward's method by using the Squared Euclidean distance measure is given.

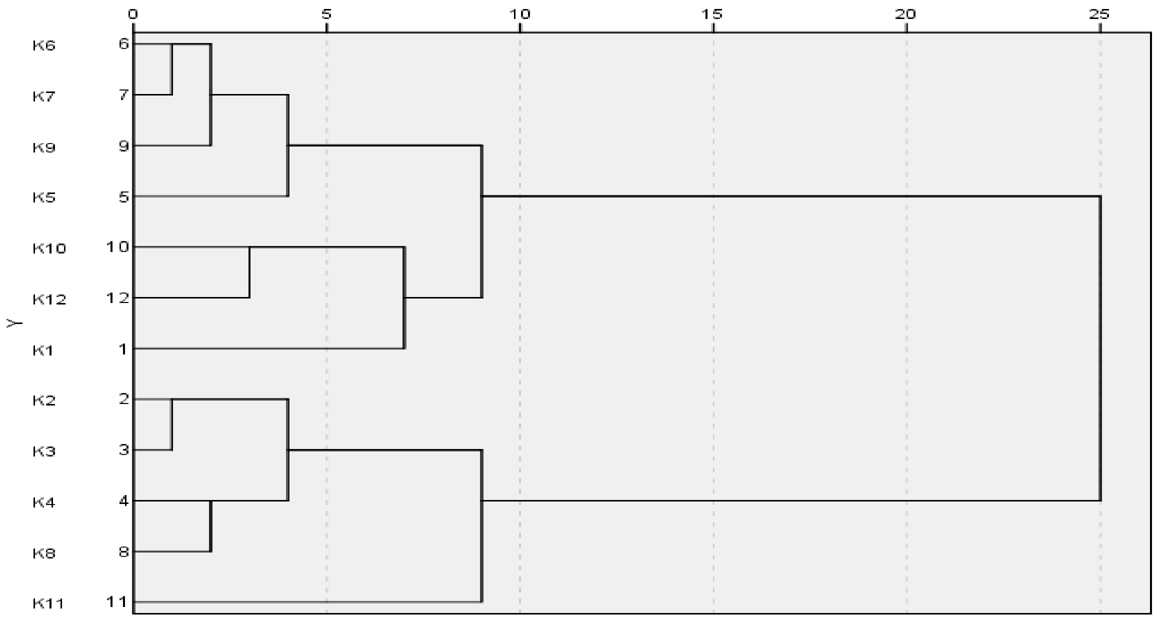

Figure 1. *The dendrogram was obtained according to Ward's method using the Squared Euclidean distance measure*

In Figure 1, the Dendrogram obtained by making the clustering analysis according to Ward's method by using the Squared Euclidean distance measure is given. As can be seen, in general, 2 clusters (factors) consisting of 5 items and 7 items are seen.

Table 5. *Minkowski distance measure*

	Factor-1	Factor-2	χ^2/df	RMSEA	CFI	NNFI	AGFI
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.09	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Nearest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Furthest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93

Centroid	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Median	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Ward Y.	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93

According to the findings in Table 4, the cluster analysis method obtained using the Minkowski distance and the EFA results are generally similar. In general, the results are similar (χ^2/df =1.78; RMSEA=0.04; CFI=0.96; NNFI=0.95). The worst fit values were obtained from the median and centroid methods (χ^2/df =5.47; RMSEA = 0.10; CFI = 0.79; NNFI=0.74).

Table 6. *Manhattan city block distance measure*

	Factor-1	**Factor-2**	**χ^2/df**	**RMSEA**	**CFI**	**NNFI**	**AGFI**
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.09	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Nearest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Furthest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Centroid	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Median	2,3,4,5,6,7,8, 9,10,11,12	1	3.37	0.07	0.86	0.83	0.87
Ward's	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93

According to the findings obtained in Table 6, the best fit values were obtained from Average linkage, Nearest Neighbor and Ward methods (χ^2/df =1.78; RMSEA=0.04; CFI=0.96; NNFI=0.95), the lowest fit values were obtained from the Median (χ^2/df =3,37; RMSEA=0.07; CFI=0.86; NNFI=0.83) and Centroid methods (χ^2/df =5,47; RMSEA=0,10; CFI=0,79; NNFI=0,74).

Table 7. *Chebyshev distance measure*

	Factor-1	**Factor-2**	**χ^2/df**	**RMSEA**	**CFI**	**NNFI**	**AGFI**
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.09	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Average Linkage	1,2,3,4,5,6,7,9,10,11,12	8	3.76	0.07	0.84	0.80	0.87
Nearest Neighbor	1,2,3,4,5,6,7,9,10,11,12	8	3.76	0.07	0.84	0.80	0.87
Farthest Neighbor	2,4,6,7,9,10,12	1,3,5,8,11	4.40	0.08	0.82	0.77	0.83
Centroid	1,2,3,4,5,6,7,9,10,11,12	8	3.76	0.07	0.84	0.80	0.87
Median	1,2,3,4,5,6,7,8,10,11,12	9	5,82	0.10	0.70	0.62	0.80
Ward's	6,7,9,10,12	1,2,3,4 5, 8,11	1.78	0.04	0.96	0.95	0.93

According to these findings, clustering methods other than Ward method generally have low fit values (χ^2/df =1,78; RMSEA=0,04; CFI=0,96; NNFI=0,95). In particular, the clustering results with the lowest fit level were obtained from the Median method (χ^2/df =5,82; RMSEA=0,10; CFI=0,70; NNFI=0,62). Similar to other findings, the factors obtained from EFA have good fit values (χ^2/df =1,78; RMSEA=0,04; CFI=0,96; NNFI=0,95).

Table 8. *Pearson similarity measure*

	Factor-1	Factor-2	χ^2/df	RMSEA	CFI	NNFI	AGFI
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.09	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Nearest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Furthest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Centroid	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Median	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Ward's	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93

According to these findings, the fit values of the factor structures obtained from all Hierarchical clustering methods are at a good level except for the Median method (χ^2/df =5,47; RMSEA=0,10; CFI=0,79; NNFI=0,74).

Table 9. *Cosine similarity measure*

	Factor-1	Factor-2	χ^2/df	RMSEA	CFI	NNFI	AGFI
Original version of the scale	1,2,3,4,5,6,7,8,9,10,11,12		4.79	0.09	0.79	0.75	0.82
EFA	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Average Linkage	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Nearest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Farthest Neighbor	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Centroid	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93
Median	1,2,3,4,5,6,7,8,9,10,12	11	5.47	0.10	0.79	0.74	0.80
Ward's	1,5,6,7,9,10,12	2,3,4,8,11	1.78	0.04	0.96	0.95	0.93

In Table 9, the results obtained according to the findings obtained by using the Cosine similarity measure are similar to the Pearson similarity measure. According to these findings, the fit values of the factor structures obtained from all Hierarchical clustering methods are at a good level except for the Median method (χ^2/df =5,47; RMSEA=0,10; CFI=0,79; NNFI=0,74).

CONCLUSION and DISCUSSION

In this study, it was aimed to compare the results obtained by using different distance and similarity measures in Hierarchical cluster methods, which are among the statistical techniques used to reveal the factor structures of the scales. According to the findings obtained within the scope of the research, the following results have been reached in general.

The fit values of the factor structures obtained in the hierarchical cluster methods are generally at a good level in the Average linkage, Furthest neighbor, Nearest Neighbor, and Ward's method. However, the fit values of the factor structures obtained from the Centroid and Median methods are not generally at acceptable fit levels. The methods that give the best factor structure in Hierarchical clustering methods used within the scope of the research are the Average linkage and Ward's method.

Similar to the research findings, Milligan (1981) stated that the two methods that give the best results in cluster studies are the Average linkage and Ward's method. Tay-Lim (1999) stated that the two methods that give the best results in determining the dimensionality in the tests by cluster analysis methods are Average linkage and Ward's method, and when these two methods are compared, Ward's method gives better results.

The EFA results are the same as the results obtained by the Average linkage, Ward's, Furthest neighbor, Nearest neighbor methods. In parallel with the research findings, Doğan and Başokçu (2010) concluded that the factor structures obtained in the EFA and Ward's methods they applied to determine the factor structure of the statistical attitude scale were very similar to each other.

When the distance and similarity measures are compared, the clustering results obtained by using Euclidean, Squared Euclidean, Minkowski, Manhattan City Block, Pearson, and Cosine methods are similar in all Hierarchical methods in general. In parallel with these findings, Tonbak (2006) concluded that Euclidean, Squared Euclidean, and Manhattan City Block methods produced similar results for continuous data in his research on distance and similarity measures used in cluster analysis. Similarly, Dinler (2014) stated that these methods generally produce similar results in his research to compare cluster analysis and distance/similarity measures.

Within the scope of the research findings, it is seen that the measures that give the best factor structure when used in all methods are Pearson and Cosine similarity measures. In parallel with these findings, De Souto, Costa, De Araujo, Ludermir & Schliep (2008), in their simulation study comparing cluster analysis methods and distance/similarity measures, concluded that Pearson and Cosine similarity measures were the measures that gave the best results in almost all methods used within the scope of the research. Similarly, Strehl, Ghosh & Mooney (2000) stated that the method that gives the best results is the Cosine method.

Factor structures created using the Chebyshev distance measure have generally low fit values in all Hierarchical clustering methods except for Ward and Average linkage. However, this may vary depending on the data structure used and the relationship status of the variables with each other. While the techniques gave different results if the distance measures used in the researches changed, the measurements gave different results if the techniques changed. In cluster analysis, not only the choice of distance measure but also the choice of the technique is equally important (Tay-Lim, 1999; Ergüt, 2011).

The comments made within the scope of this research were evaluated only according to the results obtained from the statistical methods used to examine the factor structure of the scales. However, besides the statistical knowledge of scale development, the theory of interest also requires a good level of knowledge of psychological structure. Since the results obtained from EFA and Hierarchical clustering methods were compared with this research, the characteristics of the scale such as item structure, naming, and significance of factors, etc. were not taken into account.

Some suggestions have been made based on the findings obtained within the scope of the research;

- When researchers will perform cluster analysis on any educational continuous data, it will be practical in terms of time and effort to first prefer the Pearson and Cosine method, which is one of the distance and similarity measures, and the Average linkage and Ward's method in hierarchical clustering methods, to obtain the best result.

- The fact that researchers use the Average linkage and Ward's method together with EFA to reveal factor structures especially in the development of scales measuring the psychological dimension can help to discover the structure of interest in more detail.

- While the distance and similarity measure used while performing the cluster analysis affect the results, the chosen clustering approach also affects the results obtained. One of the reasons for this is the characteristics of the data set studied, such as the correlation between the variables and, the type of scale used, and whether the data are standard or not. Researchers who are interested in this subject in the future can design their research by using multiple data sets that also take into account the different correlations between variables.

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