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The Effects of Methods of Imputation for Missing Values on the Validity and Reliability of Scales

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Abstract

The main aim of this study is the comparative examination of the factor structures, corrected item-total correlations, and Cronbach-alpha internal consistency coefficients obtained by different methods used in imputation for missing values in conditions of not having missing values, and having missing values of different rates in terms of testing the construct validity of a scale. The research group of the study, which is of a basic research, consists of 200 teacher candidates who attended the Department of Elementary Education at Ankara University, Faculty of Educational Sciences during the 2008-2009 Academic Year's spring term. The data were gathered by the Fatalism Scale (Şekercioğlu, 2008), and exploratory factor analysis based on principal component analysis method was used. The findings showed that the "single factor" structure of the scale, whose construct validity was examined in the context of the study, was also found as "single factor" when it was obtained by the original data set having no missing values in situations of imputation for missing values with different methods whereas it also caused decrease in explained variance for imputation for missing values. A similar decrease was also seen in eigenvalues and Cronbach-alpha internal consistency coefficients.

Key Words

Missing Value, Imputation, Construct Validity, Reliability.

There are incomplete data in many study contexts. These empty or unanswered values in data sets are named missing values (data), and are of a problem most researchers face. Even though researchers try to get complete data sets, it would not be wrong to imply that this problem is frequently faced in situations that participants' data are gathered by scales based on the self-report technique.

Missing data may occur from various reasons. For instance, accidentally, participants might leave some questions unanswered in long questionnaires; mechanical failures may cause unrecorded data in experimental processes or procedures or the research may be about a sensitive issue (for instance, sexual behavior), and the participants may use their right not to answer these sorts of questions (Field, 2005). Garson (2008) groups these reasons as fatigue, sensitivity, lack of knowledge, and other reasons, adding that there can also be missing data caused by missing records in some information obtained from archives. In addition to these reasons, as stated by Van der Ark and Vermunt (2007), there might be respondents who cannot get to some questions in speed tests because of the lack of time. Additionally, the respondents may leave some questions unmarked for they may not know the answer or avoid predicting in the performance tests (Finch & Margraf, 2008). To sum up, scales aiming to determine the cognitive, affective, and behavioral qualities might include missing values based on the reasons mentioned above which may affect the validity and reliability of the scores obtained from such scales.

The seriousness of the missing value problem varies depending on the fact that it has a pattern or not, to what extent the data have missing values, and why they appear as missing. It is a more serious problem for the missing values to have a pattern

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than the amount of the missing values (SPSS, 2007; Tabachnick & Fidell, 1996). If there are few missing values performing a random pattern in large data sets, the problem is not so serious and using different methods in removing missing values will cause similar results. However, having many missing values in small and medium size data sets causes serious problems. Unfortunately, there is not a criterion in the situations when deciding how many missing values will be tolerated for which sample sizes (Tabachnick &Fidell, 1996). Researchers may use alternative methods in handling missing values. It is possible to study these methods under three basic groups:

Defining one or More Value(s) instead of the Missing Value, and Excluding These Data from Analysis: It can be defined in computer programs that a datum is a missing value for a participant. Therefore, computer programs ignore this value defined; in other words, they do not include them into the analyses (Field, 2005).

Deleting Subjects and Variables Including Missing Value: Another way to interfere into missing values is to delete the subjects or variables causing problems for they have missing values. Each subject including a missing value is excluded from the data file. If only a few subjects have missing values, then deleting is a good alternative (Mertler & Vannatta, 2005). However, Carpita and Manisera (2008) emphasize that deleting the subjects causing problems for including missing values may result in data loss, and depending on the amount of missing values, it may also cause important bias because of the likely systematic differences between those who answer and those who do not.

Another option is that the missing values have grouped in few variables. In this situation, if the variable(s) is/are not important and basic variables in terms of research problem, it can be considered to delete (exclude from the data set) variables. However, if the variables are distributed throughout the data set and there are numerous, deleting subjects and/or variables cause serious data loss (Mertler & Vannatta, 2005). Tabachnick and Fidell (1996) state that this situation may cause serious problems particularly for the groups in experimental patterns, because excluding even one subject from the data set will require corrections related to the unequal *n* numbers. Moreover, if the subjects who have missing values do not distribute randomly, deleting these data may result in skewness of the distribution as well. For these reasons, Fox-Waslylyshyn and El-Masri (2005) point out that, unlike the deleting process, imputation for missing values is a process that helps sample size protected.

Predictions of Missing Values/Imputation: Another way to interfere into missing values is to make predictions of missing values and use these values in basic analyses. However, predictions and imputation processes can only be applied for quantitative variables. Three most common methods to make these predictions (imputation) are "prior knowledge", "average (mean) value imputation", and "regression" (Mertler & Vannatta, 2005; Tabachnick & Fidell, 1996).

Using prior knowledge is researchers' imputation of new values into missing values based on previous knowledge (Mertler & Vannatta, 2005). Another alternative related to missing value estimation is to calculate the mean using data obtained, and imputing these means for variables that have missing values. This process is applied before the basic analyses. If the researcher does not have other information, average value imputation is the best way of estimation. The third alternative to deal with or estimate the missing values is to use the regression approach. In regression, one or more independent variables are taken into process in order to develop an equation that can be used in imputing the dependent variable's value. A variable that has missing values in missing value estimation process becomes the dependent variable. Subjects who have complete data are used to develop this estimation equation. Once the equation is obtained, it is used to estimate the missing values in dependent variable for subjects who have missing data (Tabachnick & Fidell, 1996).

Garson (2008) states that there is not a simple rule in unintervention of missing values, deleting individuals who have missing values or imputation expressing deleting individuals that have missing values will not be a problem in case there are missing values less than 5% in large samples. Howell (2009) emphasizes that there are both advantages and disadvantages of each of method related to missing values, and that these should be taken into consideration.

According to Huisman (2000), there are many different ways to discuss missing values, and imputation is one of the most popular strategies in dealing with missing values in the items in a scale. In imputation process, empty data in the data set is filled with estimated values. However, imputation for missing values is sometimes dangerous. Huisman (2000) states that Dempster and Rubin (1983) express this situation as follows: At first, imputation seems to be a seductive idea for researchers, yet it is also a dangerous. It is seductive because it relieves the researcher for the belief that the data should be complete is a pressure on the researchers. On the other hand, it is dangerous since analysis results might be biased in case there are systematic differences between those who answer and those who do not, therefore there can easily be wrong results. Despite its danger, "imputation" is a popular technique because it gives the researchers the opportunity to work with a complete data set. However, imputation processes which are inexpertly conducted may cause much worse results than doing nothing. For this reason, one should be aware (Huisman, 2000).

There are five different options of imputation in SPSS, and the imputation methods handled in this study are limited to these five options. These methods can be briefly summarized as (Mertler & Vannatta, 2005):

1. Series Mean: It is the mean of all subjects related to a certain variable, and it is the default value in the program.
2. Mean of Nearby Points: It is the mean of nearby (surrounding) values. The number of nearby values can be found by using "span of nearby points" option. The default value in the program appears as "2 digits". In other words, arithmetical mean is calculated by using complete observation values under and above the missing data, and this value is imputed instead of the missing data.
3. Median of Nearby Points: It is the median of the nearby (surrounding) values. The researcher can also determine the number of the surrounding values. In other words, median is calculated by using complete observation values under and above the missing data, and this value is imputed instead of the missing data.
4. Linear Interpolation: This value is the imputation of the last complete observation value before the missing data and the first complete observation value after the missing value instead of the missing data. If the first and last observations are missing in the set, there cannot be any values imputed instead of the missing value.
5. Linear Trend of Point: The value is consistently determined in accordance with the trend the current structure (for instance, if the values tend to increase from the first subject to the last) performs. Missing data are placed into the values decided in an index variable where the sets are scaled from 1 to *n*.

When studies in other countries on missing value issue are examined, many of them are available. For example, Raymond and Roberts (1987) compared handling methods for missing values (missing data sets) in some selected studies. Fichman and Cummings (2003) studied multiple imputation in multivariate analysis, Grung and Manne (1998); Sanguinetti and Lawrence (2006); Raiko, Ilin and Karhunen (2007) studied missing value issue in principal component analysis, Carpita and Manisera (2008) studied missing value imputation in research with Likert type scales, and Robitzsch and Rupp (2009) studied the effect of missing values on determining differential item functioning (comparison of Mantel–Haenszel and logistic regression techniques). However, in those studies, the examination of missing values or missing value procedure was different from those in the present study. As described below, missing values were generally considered and examined as "Missing Completely at Random-MCAR", "Missing at Random-MAR" and "Missing not at Random-MNAR" mechanisms. For instance, in a study by Shrive, Stuart, Quan and Ghali (2006), 1580 participants were given the Zung Depression Scale, which was answered from 1 to 4 and those with scores higher than 40 were described as individuals with depressive syndromes. For missing values, "Missing Completely at Random-MCAR", "Missing at Random-MAR" and "Missing not at Random-MNAR" mechanisms were examined and six different imputation methods were studied. These methods were multiple imputation, single regression, individual mean, overall mean, participant's preceding response and random imputation from 1 to 4. As a result, multiple imputation method was the best to use. Also, it was concluded that individual mean imputation was an eligible method and easy to interpret.

When studies in Turkey on missing value issue are examined, it is clear that there is no direct research on missing value issue although missing values have been mentioned in some data mining research (Kızılkaya-Aydoğan, Gencer, & Akbulut, 2008). Only in a study by Oğuzlar (2001) where 7452 observation values and 21 constant variables from a 54-variable-data base about 207 countries on the World Bank webpage were included, listwise data deletion, pairwise data deletion, EM, regression imputation techniques and missing value mechanisms in SPSS were examined. Missing value mechanisms were discussed as "MCAR", "MAR" and "Nonignorable-NI" and what mechanisms were to include the available missing values were defined.

In the light of the above mentioned discussions, examining missing value issue constitutes the problem of this study in terms of testing construct validity and reliability of a scale. Generally, in social science research and especially educational and psychological studies, frequently developed scales, data collection by defining technical qualities of scales such as validity and reliability or using the available scales and presentation of results show that it is essential to examine to what extent missing values affect the procedure. The fact that there is no research in Turkey on missing value issue in related fields within the framework of technical qualities highlights the need for proper examination.

Aim

General aim of this study is the comparative examination of the corrected item-total correlations, Cronbach-alpha internal consistency coefficients and the factor structures obtained by the different methods (Series Mean Imputation, Mean of Nearby Points Imputation, Median of Nearby Points Imputation, Linear Interpolation, Linear Trend of Point) used in imputation for missing values in the condition where there are not any missing values and in the conditions where there are missing values of different rates (ranged approximately 15.00%-20.00% and 0.00%-50.00%) in terms of testing the construct validity of a scale.

Method

Research Model and Group

The research is about the comparison of exploratory factor analysis results obtained by the principal components analysis method used in determining factor structures of scales under conditions of imputation for missing values by different methods. For this reason, the study is a basic research defining theoretical studies on information production. The research group consists of 200 teacher candidates who attended the Department of Elementary Education at Ankara University Faculty of Educational Sciences during the 2008-2009 Academic Year's spring term.

Instrument

Data of this study were gathered by the Fatalism Scale. The Fatalism Scale, whose validity and reliability studies were conducted on a group of teacher candidates by Şekercioğlu (2008), consists of 10 items grouped under a single factor. Besides, it was found that this single-factor structure obtained by the exploratory factor analysis was also confirmed by the confirmatory factor analysis. The scale, which has a 5-point Likert-type format, is scored as "completely inappropriate (1)" to "completely appropriate (5)." Therefore, higher scores define higher fatalistic thinking level. The Cronbach-alpha internal consistency coefficient of the Fatalism Scale was found .81. The test-retest reliability obtained by two applications conducted on a group of 40 people within four weeks was found as $r = .88$ ($p < .01$).

Analysis

Exploratory factor analysis based on principal components analysis method was applied in order to test the construct validity of a scale under different conditions related to missing values in this study. Moreover, item-total correlations and Cronbach-alpha internal consistency coefficients for different conditions were also estimated.

Procedure

First, exploratory factor analysis application based on principal components analysis method was applied with the original data set (n=200) that did not have missing values in order to achieve the aim of the research. Afterwards, by random deleting of some data from the data set, a data set that had missing values was obtained. The first data set includes missing values varying approximately between ranges of 15.00% and 20.00% related to the variables (items) whereas the second data set includes missing values varying approximately between ranges of 0.00% and 50% related to the variables (items). Before the imputation processes were realized assuming that the missing values were randomly distributed throughout the variables in both data sets.

Findings

Findings of the First Data Set

The first data set includes missing values varying between ranges of 15.00% and 20.00%. When the findings of factor analysis realized by this data set were generally evaluated, the item with the lowest factor loading was the 6th item in condition where there were not missing values and where there were imputed for missing values by different methods. It should be remembered that the 6th item showed a factor loading less than .30 under the "Linear Interpolation" condition, and it was excluded from the scale for this reason. The item with the highest factor loading under all conditions was the 5th item. The 9th and the 5th items had equal and highest factor loadings in the original data set without missing values whereas this situation was not seen again under any conditions.

When the eigenvalues and explained variances were evaluated, it was seen that the highest values were obtained in the condition without the missing values. Imputation for missing values caused a decrease in variance rates. The condition where the lowest variance was explained was the "Linear Interpolation" condition whereas the condition where the highest variance was explained was the "Linear Trend of Point" condition. However, when the 6th item in the "Linear Interpolation" condition was excluded, it was seen that the lowest explained variance rate appeared under the Median of Nearby Points Imputation condition.

When findings of corrected item-total correlations and Cronbach-alpha internal consistency coefficient estimated by the first data set were evaluated, it was seen that the lowest range of the corrected item-total correlations varied between .20 and .38, and the highest range of the corrected item-total correlations varied between .59 and .79. However, when the range was evaluated with the item-total correlations obtained for the factor structure repeated in order to exclude item 6 from the scale under "Linear Interpolation" condition, it was seen that the lowest range of the corrected item-total correlations varied between .22 and .42. Cronbach-alpha internal consistency coefficients' range varied between .78 and .85. Imputation for missing values caused a decrease in Cronbach-alpha internal consistency coefficients as it did in eigenvalues and variance rates.

Findings of the Second Data Set

The second data set includes missing values varying between ranges of 0.00% and 50.00%. When the findings of factor analysis realized by this data set were generally evaluated, the item with the lowest factor loading was the 6th item under all conditions whereas the item with the highest factor loading was the 5th item. However, it should be remembered that the 6th item showed a factor loading less than .30 under the imputed "Mean of Nearby Points" and "Median of Nearby Points", and "Linear Interpolation" conditions, and it was excluded from the scale. When the analyses were repeated for these conditions, the item with the lowest factor loading was the 10th item under all conditions whereas the item with the highest factor loading was the 5th item, again.

When the eigenvalues and explained variance values were evaluated, it was seen that the highest values were obtained in the condition without the missing values. Imputation for missing values caused a decrease in variance rates. The condition where the lowest variance was explained was the "Linear Interpolation" condition whereas the condition where the highest variance was explained was the "Linear Trend of Point" condition. However, when the analyses were repeated under "Mean of Nearby Points", "Median of Nearby Points", and "Linear Interpolation" conditions with the exclusion of the 6th item, it was seen that the lowest explained variance rate appeared under the "Series Mean" imputation condition.

When findings of corrected item-total correlations and Cronbach-alpha internal consistency coefficient were evaluated, it was found that the lowest range of the corrected item-total correlations varied between .19 and .51 before the 6th item was excluded, and .25 and .51 after the exclusion. It was also seen that the highest range of the corrected item-total correlations did not become different according to the 6th item's inclusion or exclusion, yet varied between ranges .56 and .90. When Cronbach-alpha internal consistency coefficients were examined, it was found that they varied between .77 and .91, and that there was no difference seen in this range after the exclusion of the 6th item.

Discussion and Results

In this study, a comparative examination was conducted on the factor structures obtained by the different methods (Series Mean Imputation, Mean of Nearby Points Imputation, Median of Nearby Points Imputation, Linear Interpolation, Linear Trend of Point) used in imputation for missing values in the condition where there were not any missing values and in the conditions where there were missing values of different rates in terms of testing the construct validity of a scale. Moreover, corrected item-total correlations and Cronbach-alpha internal consistency coefficients related to the factor structures obtained under different conditions in both data sets having different rates of missing values were found.

When the findings were evaluated, it was seen that the examined scale's "single-factor" structure obtained by the original data set without missing values was also obtained as "single-factor" for the conditions of imputation for missing values by using different methods.

The first data set included missing values varying between ranges of 15.00% and 20.00%. In the analyses realized on this data set, an item under the "Linear Interpolation" condition was excluded from the scale for it showed low factor loading. Therefore, it was found that the 10-item scale performed with 9 items under this condition. The second data set included missing values varying between ranges of 0.00% and 50.00%. In the analyses realized on this data set, it was determined that an item that did not work under the "Linear Interpolation" condition in the first data set would be excluded from the scale since it showed low factor loading under "Mean of Nearby Points", "Median of Nearby Points", and "Linear Interpolation" conditions. There was an important point in analyses with both data sets. Although the study did not attempt to develop a scale, the reason for item exclusion from the scale was to emphasize the changes in factor structure of the scale under different conditions. It was thought that factor analysis needed to be repeated following the item exclusion from the scale to observe such changes in accordance with the aim of the study.

When the findings of exploratory factor analyses based on principal components analysis method realized by the two data sets having different missing value rates are generally evaluated, it can be stated that the items having lowest and highest factor loadings show consistency in almost all conditions. A similar situation is at hand in corrected item-total correlations. The most important situation observed in the construct validity examinations conducted in this study is that imputation for missing values cause decrease in explained variance rates. It can be pointed out that this situation, which has been emphasized as being related to the mean imputation by Mertler and Vannatta (2005) in literature, was observed in all imputation conditions. Besides, same situation is observed in eigenvalues and Cronbach-alpha internal consistency coefficients. In other words, imputation causes a decrease in aforementioned values. In case of a low number of missing values in data, data deletion might not affect the sample power to represent the population. However, when there is a high percentage of missing values in the data set, disregarding such data may reduce the reliability of model structure and model estimations (Satıcı and Kadılar, 2009). In the literature, there are methods such as missing value imputation, series mean imputation, imputation for data production by another variable, nearby points imputation and weighted methods (Satıcı, 2009). In this study, missing value imputation was performed by using series mean imputation, imputation for data production by another variable (median, mode), imputation by data production, and imputation by nearby data production methods. It was observed that factor structure of the scale was degenerated in such imputations and there were decreases in both explained variance and reliability criteria. In the literature, it was reported that the methods led to systematic errors (Satıcı, 2009). For the study, it might be thought that systematic errors had a direct effect on construct validity of the scale and an indirect effect on reliability. Donders, Heijden, Stijnen and Moons (2006) suggested that data production by neighborhood might lead to biased or deviant findings. Missing observations similar to nearby observations occasionally lead to consistent outcome production and they sometimes cause data production inconsistent with both within-case complete observations and complete data set cases.

The study examined effectiveness of commonly used imputation methods. In the literature, there have been arguments that there are more effective methods to produce more realistic results. Over the recent years, there have been studies which claim that data production by the examined "Hot Deck Imputation", "EM (Expectation Maximization)" and "Regression Method" is more effective than data production by classical methods" (Kayaalp & Polat, 2001; Özel & Ata, 2007; Satıcı & Kadılar, 2009). When higher prospect of biased data production by classical method is considered, further research where other imputation methods are used as suggested in the literature is recommended and a comparative study of these methods will contribute to the use and extension of the methods.

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