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Focus on Research Methods

Handling Missing Data in Self-Report Measures

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Abstract: Self-report measures are extensively used in nursing research. Data derived from such reports can be compromised by the problem of missing data. To help ensure accurate parameter estimates and valid research results, the problem of missing data needs to be appropriately addressed. However, a review of nursing research literature revealed that issues such as the extent and pattern of missingness, and the approach used to handle missing data are seldom reported. The purpose of this article is to provide researchers with a conceptual overview of the issues associated with missing data, procedures used in determining the pattern of missingness, and techniques for handling missing data. The article also highlights the advantages and disadvantages of these techniques, and makes distinctions between data that are missing at the item versus variable levels. Missing data handling techniques addressed in this article include deletion approaches, mean substitution, regression-based imputation, hot-deck imputation, multiple imputation, and maximum likelihood imputation. © 2005 Wiley Periodicals, Inc. Res Nurs Health 28:488–495, 2005

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Missing data is a common problem in research, particularly when data collection involves the use of self-report measures. In self-report measures, data can be missing at either the *item* or *variable* level. Item level missingness occurs when subjects omit one or more items within a multi-item instrument that measures an abstract concept or variable (e.g., depression). Variable level missingness occurs when *all* items on a multi-item instrument are missing. However, many variables (e.g., age and gender) are measured with single-item questions. Missing values on such single-item variables are conceptualized here as variable level missingness. Therefore, our reference to variable level missingness in this article includes data that are missing on single-item variables such as age, as well as missingness on entire multi-item instruments.

Missing data at both the item and variable levels pose a problem because loss of data can lead to loss of statistical power and bias in parameter estimates (Roth, 1994). When data are missing, standard analysis techniques cannot immediately be used to analyze an incomplete data set because most statistical procedures require a value for each variable/item (Allison, 2000; Rubin, 1987). Thus, the default in many statistical programs is deletion of cases with missing data. A variety of statistical techniques are available to treat missing data. While the basic techniques for handling both

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levels of missing data are similar, the implications of each may be somewhat different (Roth & Switzer, 1999). The purposes of this article are to provide researchers with a conceptual overview of the types of missing data and to describe the primary approaches used in handling missing data. With the exception of mean substitution, the techniques described in this article are appropriate to treat missing data measured at nominal, ordinal, and interval levels. Sample and group mean substitution should only be applied to treat missingness in variables that are measured at the interval level. However, case mean substitution can be used to impute ordinal missing data such as in Likert scales.

EXTENT AND PATTERN OF MISSING DATA

When faced with missing data, it is important to determine both the extent and pattern of missingness because these factors impact the validity of research findings. The extent of missing data refers to the percentage of cases with missing data on a given item or variable. To date, no empirical guidelines are present to suggest what constitutes excessive missingness. However, Cohen and Cohen (1983) suggested that when up to 10% of cases have missing data on a given variable, the extent of missing data is not extensive, and thus the variable should be retained and the missing data should be treated. Hertel (1976) suggested that a variable should be deleted when 15% or more of the cases have missing data on that variable. Raymond and Roberts (1987) recommended a more liberal estimate and suggested that a variable should be deleted when 40% or more of the cases have missing data on a specific variable.

Tabachnick and Fidell (2001) and Kline (1998) suggested that the pattern of missing data is more important than the extent of missingness because it has a larger impact on the generalizability of results. Based on whether missing data are dependent on observed values, patterns of missing data are classified into three categories: systematic, missing completely at random (MCAR), and missing at random (MAR). When a missing data point is not dependent on other variables in the data set, but is dependent on the unobserved missing value itself, missingness is assumed to be systematic or not missing at random (Heitjan, 1997; Kline, 1998). Suppose, for example, that a group of adolescents were enrolled in a study to examine the impact of acne treatment on self-esteem. During the first session, participants were classified as having minor, moderate, or severe acne. If participants who had no improvement in their acne decided to withdraw after the first treatment session because they did not see a benefit in participating, then missingness on the follow-up measure of acne improvement is related to the missing value itself (acne improvement) and is said to be systematic. When the probability of missing data on a given variable is independent of the values of that variable, and of the values of other variables in the data set, the data are assumed to be MCAR (Heitjan, 1997; Patrician, 2002). Using the previous example, the pattern of missingness is assumed to be MCAR if follow-up data on acne improvement is missing only because some participants could not attend a follow-up session due to reasons such as illness or being unable to secure transportation. When the probability of non-response is independent of the missing value, but is related to the values of another variable in the data set, the data are considered to be MAR (Kline; Little & Rubin, 1987). Thus the pattern of missingness would be MAR if participants who were diagnosed as having severe acne in the first session decide not to attend the follow-up sessions because of embarrassment concerning their initial acne severity, regardless of whether or not their acne had improved. In this case, the missingness is not related to the missing value itself (acne improvement), but is related to another variable in the data set (initial acne severity). Both MCAR and MAR assume that missing data are not related to participants' true scores on the variable with missing data. However, the definition of MCAR carries a stronger assumption that missing data are truly random (Kline; Patrician).

Approaches to Determining the Pattern of Missing Data

Failure to examine the pattern of missingness may yield biased parameter estimates that may produce invalid results, especially if the pattern of missingness is systematic. Unfortunately, data often provide little or no information to allow confirmation of the pattern of missingness (Heitjan, 1997; Rubin, 1987). Nonetheless, several techniques are available to help investigators examine the pattern of missing data (Cohen & Cohen, 1983; Orme & Reis, 1991). These techniques enable investigators to rule out, but cannot confirm, the assumption that data are MCAR. For example, a researcher who finds no systematic explanation for missing data may be tempted to infer that data are MCAR. However, it is quite possible that the values of the missing data are related only to themselves or to other unknown extraneous or unmeasured factors. Neither of these two possibilities can be tested because the investigator has no access to the missing values (Allison, 2000; Huisman, 1998).

One way to explore the pattern of missingness is to create a missing data dummy code (*missing value* = 0; *non-missing value* = 1) and correlate it with the other variables in the data set (Acock, 1997; Cohen & Cohen, 1983). A significant strong correlation indicates that missing data are related to other variable(s) in that data set and therefore cannot be MCAR. Although a significant marginal correlation could indicate that data are not MCAR, it could also be a function of a large sample size (Musil, Warner, Yobas, & Jones, 2002). Unfortunately, there is no standard cut-off point at which a correlation coefficient indicates that data are missing randomly.

A second approach involves creating a missing data dummy code and computing *t*-test comparisons between respondents and non-respondents to examine if they are different on any of the variables or items in the data set (Acock, 1997; Huisman, 1998). For categorical variables, Chi-square can be used instead of *t*-test. A significant difference between respondents and non-respondents indicates an association, and rules out the possibility that the data are MCAR (Huisman). It is important that sample size be considered in this approach because *t*-test is sensitive to sample size, and the absence of a statistical difference could be a function of small sample size.

A superior approach to crude bivariate correlations and *t*-test comparisons involves running a predictive logistic regression model in which the missing data dummy variable is treated as a dependent variable (Hair, Anderson, Tathman, & Black, 1998; Little & Rubin, 1987; Weinfurt et al., 2003). This approach enables investigators to assess the adjusted impact of other variables in the data set on the missing data variable. Suppose, for example, that the investigators in the acne study collected data on age, acne severity, acne duration, and previous acne treatment, but some respondents failed to report if they had previously sought acne treatment. The investigator would create a missing data dummy variable (*report* = 1, *no report* = 0) that could be entered as the dependent variable in a predictive logistic regression model to determine if this variable can be predicted by acne severity, acne duration, and/or age. If the dummy variable is predicted by any of these variables, missing data cannot be assumed to be MCAR. A disadvantage of this procedure is that regression coefficients can be inflated when other variables in the data set are used to predict the incomplete observations (Hair et al.); this problem can be magnified when multi-collinearity is an issue. Inflation of the regression coefficients can lead to invalid conclusions about the pattern of missingness. The seriousness of this problem depends on the sample size and the amount of missing data (Musil et al., 2002).

Another regression-based approach involves using the missing data dummy variable as an independent variable in a regression model and including the information concerning the presence or absence of missing data in the actual analysis (Orme & Reis, 1991). According to this approach, variables with complete observations and the missing data dummy variable are entered in a regression model to partial out the effect of the variables with complete data from the relationship between the missing data variable and the outcome variable. In other words, it allows investigators to examine the relationship between missing data and the outcome variable while holding other variables constant. If the missing data variable predicts the outcome variable, then data cannot be MCAR. In addition to determining the pattern of missing data, this approach has the advantage of maintaining statistical power, reducing bias, and providing meaningful information on the possible correlates of missing data (Orme & Reis). Orme and Reis cautioned that a zero correlation between a missing data variable and the outcome variable indicates only that the missing data are not related to the dependent variable; one cannot infer that the obtained values on the predictor variables are a random subset of the sampled values. Thus, this approach may rule out, but cannot confirm that data are MCAR.

TECHNIQUES FOR HANDLING MISSING DATA

Missing data can be handled by either deletion or imputation techniques (Kline, 1998; Little & Rubin, 1987). Deletion techniques involve excluding subjects with missing data from statistical calculations. Imputation techniques involve calculating an estimate of each missing value and replacing, or imputing, each value by its respective estimate. Techniques for handling missing data often vary in the degree to which they affect the amount of dispersion around true scores, and the degree of bias in the final results (Roth & Switzer, 1995). Therefore, the selection of a data handling technique should be carefully considered.

Deletion Techniques

Deletion techniques can take the form of either listwise or pairwise deletion. Listwise deletion eliminates an entire case when any of its items/variables has a missing data point, whether or not that data point is part of the analysis (Kline, 1998; Tabachnick & Fidell, 2001). Pairwise deletion eliminates a case only when that case has missing data for variables or items under analysis. Deletion techniques are widely criticized because they assume that the data are MCAR (which is very difficult to ascertain), pose a risk for bias, and lead to reduction of sample size and power (Little & Rubin, 1987; Roth, 1994; Schafer & Olsen, 1998; Tabachnick & Fidell, 2001). Because of the problems that are inherent in the use of deletion techniques, they are not further discussed in this article.

Imputation Techniques

Imputation involves replacing missing data with estimates that are based on the values of other variables/items in the data set. Unlike deletion, imputation retains sample size, thereby minimizing attenuation of statistical power. Imputation techniques are generally classified as either single or multiple. Single imputation ascribes one estimate for each missing data point, while multiple imputation ascribes several estimates for each missing data point. With the exception of multiple imputation, all the techniques discussed below are considered single imputation techniques.

Sample and group mean substitution. Sample mean substitution involves replacing a missing data point for a case on a variable/item with the sample mean score of that variable/item (Acock, 1997; Kline, 1998; Tabachnick & Fidell, 2001). This technique assumes that missing and available data are normally distributed, and that the best guess for a missing score is the mean of that variable (Acock). Group mean substitution ascribes the group (level) mean value of a missing data point within that group. It assumes that scores for different groups of a given variable are different from one another, and that scores for subjects within a group are homogenous (Acock). Although these two techniques preserve data and are easy to compute, they tend to decrease the variance-covariance between a missing data variable and the other variables (Raymond & Roberts, 1987; Roth, 1994; Tabachnick & Fidell). In addition, they tend to ascribe values that are more likely to be closer to the values of other cases than to the real missing values. Therefore, the use of sample and group mean substitution techniques should be restricted to situations in which the extent of missingness is very small and the pattern of missingness is MCAR (Roth; Tabachnick & Fidell), which is almost impossible to confirm.

Case mean substitution. Case mean substitution ascribes the subject's mean score based upon the items that are present to the missing score for that subject (Raymond, 1986). This strategy assumes that for any given case, the score on any data point is closely related to the scores on the remaining data points. Therefore, this technique is especially applicable to self-report measures in which all items are indicators of a specific concept or construct and are assumed to be closely and positively correlated. The primary advantage of this technique is that it acknowledges differences across cases by using data provided by a case to estimate its own missing data, rather than using data provided by other cases. In fact, Roth, Switzer, and Switzer (1999) found that case mean substitution was robust in handling item-level missingness when data were missing on 20% of the items, in both random and systematic patterns. Downey and King (1998) reported that, when data are MCAR, case mean substitution reproduces a robust alpha when up to 30% of items were missing. They found that correlations between original and estimated scores were greater than .95 when the number of: (a) missing items does not exceed 60%, or (b) cases with missing data do not exceed 15%. Case mean substitution may not be appropriate to impute missing data at the variable level because the combination of variables within a case often does not represent a single concept.

Hot-deck imputation. Hot-deck approaches generally involve imputing a missing data point with the score from a similar case in the sample. The two major hot-deck imputation approaches are the *distance function approach* (Roth & Switzer, 1995) and the *pattern matching approach* (Roth, 1994; Roth & Switzer). The distance function approach, also known as nearest neighbor approach, replaces missing data by measuring the squared distance statistic between the case with missing data and all other cases in the data set. Then, the score of the case that has the lowest squared distance from the case with missing data is used to replace the missing score (Roth & Switzer).

The matching pattern approach is a more common technique. First, the sample is stratified into separate homogenous groups. Then, each missing value is imputed from a randomly selected donor case in the same group that has a similar profile of scores across other variables (Ford, 1983; Kline, 1998). Using our example of the acne study, suppose two respondents have similar scores for acne severity, acne duration, and age, but only one had data on acne improvement. According to the matching pattern approach, the score on acne improvement from the respondent with complete data would be used to impute the missing value for the other case.

Proponents of hot-deck imputation suggest that it is an accurate technique because missing data are replaced by realistic scores that preserve variable distributions (Kline, 1998; Roth, 1994). However, Ford (1983) suggested that hot-deck procedures are based more on "common sense" than on theory. In addition, hot-deck imputation can be very complex and unwieldy when matching is made on a large number of variables or items (Roth). It may also lead to loss of information as a result of recoding continuous variables into categories for the purpose of stratifying the sample into separate homogenous groups. Other disadvantages of hot-deck imputation include difficulty in estimating standard errors (Roth) and underestimation of variability (Little & Rubin, 1987).

Roth (1994) reported that hot-deck imputation is appropriate when up to 20% of data are MAR or when up to 10% of data are missing in a systematic pattern. Schoier (2004) suggested that hot-deck imputation is advantageous for imputing missing data at the item level because it preserves the distribution of item values, permits the use of the same sample weight for all items, and yields results that are consistent across different analyses.

Regression imputation. Regression imputation uses knowledge of available data to predict the values of missing data. It is based on the principle that, if missing data variables can be predicted by other variables in the data set, the resulting regression equation can be used to predict missing values for incomplete cases (Acock, 1997; Patrician, 2002; Tabachnick & Fidell, 2001). Regression imputation can be conducted with a single iteration or with multiple iterations. In the single iteration approach, data on complete cases are initially used to predict the variable that has missing data and generate a prediction equation. The prediction equation is then used to predict missing data for incomplete cases (Patrician, 2002; Roth, 1994; Tabachnick & Fidell).

The multiple iterations approach uses stepwise regression to isolate the smallest combination of variables that best predict the missing data (Roth, 1994). In this approach, the values obtained from the prediction equation of the initial regression model are used to ascribe the values of missing data. These new values are then used to run a new regression model and generate a second prediction equation, and so forth. The prediction equation, resulting from each iteration, produces new estimates (unstandardized regression coefficients) that are used to revise the estimated values of missing data. The iteration process continues until there is little or no change in the regression coefficients (Raymond & Roberts, 1987; Roth; Tabachnick & Fidell, 2001).

Regression imputation strives to methodologically estimate the missing data and thus is relatively objective (Tabachnick & Fidell, 2001). It often yields reasonable estimates of means, particularly when data are normally distributed. Empirical studies indicate that regression imputation is more accurate than the previously described approaches (Raymond & Roberts, 1987). Raymond and Roberts suggested that regression is most useful when data are 10%–40% incomplete, and the variables are at least moderately correlated. Iterated multiple regression tends to be more appropriate if the extent of missing data exceeds 15%–20%. Roth (1994) suggested that regression is appropriate when up to 20% of data are MCAR, when up to 15% of data are MAR, or when up to 10% of data are missing in a systematic pattern.

Despite its strength as an empirical imputation procedure, regression imputation has several disadvantages. It can lead to over-prediction of the missing data if the explained variance (R^2) in the missing data variable was artificially high due to multi-collinearity among the predictors (Acock, 1997; Cohen & Cohen, 1983; Raymond, 1986). In addition, the predicted values may be more consistent with the variables that predicted them than with the actual values of the missing scores (Tabachnick & Fidell, 2001). Another disadvantage stems from the possibility that variables used to predict missing value(s) may not be good predictors, and may therefore lead to inaccurate estimation of the missing value(s). One way to minimize this problem is to use only the best predictor or set of predictors in the regression model that contribute the largest percentage of the explained variance in the regression model (Acock; Frane, 1976). Researchers using regression imputation methods are cautioned not to impute missing data on independent variable(s) using a prediction equation that includes the dependent variable because this may artificially inflate the R^2 (Cohen & Cohen; Raymond & Roberts, 1987). Finally, because a prediction equation is needed for each item/variable with missing data, the number of regression equations needed to impute a relatively large number of missing data points can be large and unwieldy (Roth & Switzer, 1999).

Maximum likelihood (ML) and expectation maximization (EM). ML is a model-fitting program that assumes multivariate normality (Kline, 1998). This principle makes ML a robust method for imputing data that are MAR. ML assumes that cases that provide complete data are obtained from a multivariate normal distribution from which missing data could be imputed using the estimated parameters that will result from the conditional distribution of the variables with complete data (Roth, 1994). To demonstrate how ML works, one can use the previously described acne example. Assume again that the variable acne improvement had some missing data points while the other variables had complete data. An investigator could use ML to describe the multivariate relationship among the variables and then compute missing data on acne improvement using the resulting parameter estimates. While this sounds similar to regression-based imputation, it differs in that ML uses all data points in a database to construct the best first- and second-order moment estimates. Thus, when the multivariate normality assumption is met, and the data are assumed to be MAR, ML is able to generate a superior variance-covariance matrix among the variables than that produced by regression analysis (Roth; University of Texas Statistical Services, 2000). In fact, Roth suggested that ML is appropriate to impute missing data when up to 20% of data are missing, regardless of the pattern of missingness. Despite its robustness as a technique for handling missing data, the performance of ML estimation at the item level has not been reported in the literature. This is likely because ML is primarily a structural equation modeling technique that is not widely available on conventional statistical software packages. However, ML is available in SAS under the program's *mixed* function option.

Expectation maximization (EM) algorithm is another form of ML that uses an iterative procedure in an effort to produce the best parameter estimates. It begins with estimating missing data based on assumed values for the parameters. The actual data and missing estimates are then used to update the parameter estimates, which are then used to re-estimate missing data. The process continues until there is convergence in the parameter estimates (Roth, 1994; Schafer & Olsen, 1998), which indicates that more iterations will not produce significant changes in parameter estimates (University of Texas Statistical Services, 2000). EM is considered to be a superior technique because it produces unbiased parameter estimates when data are MCAR, and less biased parameters when data are MAR or systematic (Acock, 1997). Despite its complex mathematical and conceptual foundations (Roth), EM can be easily performed using several software packages such as SPSS and LISREL.

Multiple imputation. A major disadvantage of single imputation techniques is that they treat imputed values as if they are known with certainty, or that they *are* the true values. Hence, inferences based on single imputation techniques are artificially ''precise,'' and standard errors are too small because they do not accurately reflect uncertainty about the actual values of the missing observations (Heitjan, 1997; Little & Rubin, 1987). Multiple imputation provides an empirical alternative to single imputation techniques that adds variability to the imputation process by creating different estimates for a single missing datum (Acock, 1997; Rubin, 1987). It is best described as a three step procedure in which several complete data sets are simulated, each data set is analyzed separately, and the results of all analyses are pooled together to provide one result (McCleary, 2002).

There are several possible approaches to impute missing data in the first step of multiple imputation. These include imposing a probability model such as a multivariate normal distribution or a loglinear model to estimate missing data (Schafer & Olsen, 1998). An alternative approach involves using a regression equation (Yuan, 2004). When regression is used, the first step is equivalent to imputing data using the single iteration regression imputation procedure for each missing data item/variable. Next, a random numbers generator is used to simulate a set of residuals that are added to the regression predictions, which then replace the missing values. The result is one complete data set. This step is then repeated or replicated *m* times, yielding *m* complete data sets. In the second and third steps, the intended data analysis is performed on each replicated data set, and the results of each analysis are pooled to give a single result that accounts for variability between imputations and variability within the analyses (McCleary, 2002; Rubin, 1987). The number of replications, *m*, depends largely on the degree of missing data. Rubin suggested that 3–5 repetitions are sufficient when missingness does not exceed 20%. However, because the variability of solutions across multiple imputations provides the basis for estimating standard errors (Acock, 1997), iterations should continue as long as they continue to produce significantly different estimates.

The main advantage of multiple imputation is that it reflects uncertainty about missing values, which can include uncertainty about the mechanism for non-response (Little & Rubin, 1987). Second, although multiple imputation assumes that data are MAR (Schafer & Olsen, 1998), it can be used to handle systematic patterns of missing data (Heitjan, 1997). Third, it is superior to listwise deletion, pairwise deletion, and mean substitution; and is robust to violations of non-normality of the variables (University of Texas Statistical Services, 2000). In addition, it preserves sample size and makes use of all available data (McCleary, 2002). While there is a paucity of literature on the appropriateness of using multiple imputation for handling item level missing data, Schafer and Olsen suggested that multiple imputation is suitable for both item- and variable-level missingness. Disadvantages of multiple imputation include complex and time intensive computations that may be complicated by the fact that the procedure is not available on conventional statistical software packages. However, multiple imputation is available on the NORM 2.03 software program, which can be downloaded free of charge from the internet (www.stat.psu.edu/~jls/misoftwa.html).

SUMMARY

This article provides an overview of several approaches to handling missing data at both the item and variable levels. Almost all of the missing data techniques that are discussed have advantages and disadvantages. Some procedures such as deletion techniques and mean substitution are statistically easy, but empirically weak. Others such as ML and multiple imputation are technically challenging, but tend to yield more robust estimates of missing values. The robustness of certain techniques is often dependent on the extent and pattern of missing data. It is therefore important that these factors be considered to ensure that estimation error and response bias are minimized. In fact, Tabachnick and Fidell (2001) and Roth and Switzer (1995) suggested the choice of techniques is of little importance if the amount of missing data is low (less than 5%). However, as the amount of missing data increases, and the pattern of non-response becomes systematic, there is a greater need to use imputation techniques that assume uncertainty about missing values such as multiple imputation.

It appears from our review of the nursing literature that investigators often fail to address how much data were missing, the approach used to handle the problem, and how the generalizability of their results might have been affected. Because the accuracy of parameter estimates and the subsequent validity of research results may be dependent on investigators' approach to handling missing data, we recommend that researchers inform their readers about how the problem of missing data was addressed. Such a practice would reflect the rigor of nursing research and improve readers' ability to make an informed decision regarding the validity of the study findings.

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