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A review of techniques for treating missing data in OM survey research

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Abstract

The treatment of missing data has been overlooked by the OM literature, while other fields such as marketing, organizational behavior, economics, statistics and psychometrics have paid more attention to the issue. A review of 103 survey-based articles published in the *Journal of Operations Management* between 1993 and 2001 shows that listwise deletion, which is often the least accurate technique of dealing with missing data, is heavily utilized by OM researchers. The paper also discusses the research implications of missing data, types of missing data and concludes with recommendations on which techniques should be used under different circumstances in order to improve the treatment of missing data in OM survey research.

Keywords: Missing data; Empirical research; Measurement and methodology

1. Introduction

Missing data are a very common problem in empirical research (Lepkowski et al., 1987; Downey and King, 1998) and especially in survey research because it usually involves a larger number of responses and a larger number of respondents (Kim and Curry, 1977; Quinten and Raaijmakers, 1999). However, this topic has received no coverage in operations management research. On the other hand, certain fields such as marketing (Kaufman, 1988; Kamakura and Wedel, 2000; Koslowsky, 2002), organizational behavior (Roth et al., 1999), economics, statistics (Aldrin and Damsleth, 1989; Stinebrickner, 1999) and psychometrics (Brown, 1983; Fichman and Cummings, 2003; Newman, 2003) have paid more attention to the issue.

The purpose of this article is to familiarize empirical OM researchers with the key issues of dealing with missing data in their own research. Its main goal is not to provide a step-by-step guide of how to use each technique, but instead, to provide a review of techniques for treating missing data for those OM researchers who are not very familiar with them. The paper will focus on situations in which some information is missing from an individual case rather than the total lack of response to a survey. Readers interested in techniques for improving response rates in OM survey research are referred to Frohlich (2002).

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The paper is organized as follows. We discuss the research implications of missing data, types of missing data and techniques for improving the treatment of missing data. Then, we provide an evaluation of the treatment of missing data in OM survey research, and conclude with recommendations to empirical OM researchers.

2. Missing data

2.1. Missing data: is it a big deal?

According to Roth et al. (1999), missing data have two major negative effects: first, they have a negative impact on statistical power. According to Verma and Goodale (1995):

''Even though the power of a statistical test depends on three factors [significance level, effect size and sample size] from a practical viewpoint only the sample size is used to control power. This is because the α level is effectively fixed at 0.05 (or some other value). Effect size can also be assumed to be fixed at some unknown value because generally researchers cannot change the effect of a particular phenomenon. Therefore, sample size remains the only parameter that can be used to design empirical studies with high statistical power''.

A Monte Carlo simulation by Kim and Curry (1977) found that when 2% of the data are missing randomly and the researcher deletes entire cases with any missing data (what is known as listwise deletion), this can result in a up to 18.3% loss of the total data set. According to a study by Quinten and Raaijmakers (1999), the use of listwise deletion resulted in a loss of statistical power ranging between 35% (for scales with 10% missing data) and 98% (for scales with 30% missing values).

Second, missing data may result in biased estimates (Madlow et al., 1983; Roth et al., 1999) in several ways. First, measures of central tendency may be biased upward or downward depending upon where in the distribution the missing data appear. Second, measures of dispersion may also be affected depending upon which part of the distribution has missing data. Third, missing data may bias correlation coefficients downward. The downward bias is most likely as high and/or low scores lost restrict the variance in one variable and decrease the correlation with another variable. However, it is important to emphasize the significance of theory/previous literature in expecting biased estimates. If the literature does not suggest that there are significant relationships between missing values and other variables, then a priori one should expect that there is no bias.

In summary, the potential effects of missing data depend upon: (a) why the data are missing and (b) the technique used to deal with missing data in the analysis. Both of these issues are addressed in the following sections.

2.2. Reasons and patterns of missing data

2.2.1. Reasons leading to missing data

Before any missing data remedy can be implemented, the researcher must first diagnose and understand the missing data processes underlying the missing data (Little and Rubin, 1987). Many reasons can lead to missing data. One type of missing data process that may occur in any situation is due to procedural factors, such as errors in data entry, disclosure restrictions, or failure to complete the entire questionnaire. Another type of missing data process occurs when the response does not apply (e.g., questions regarding the years of marriage for respondents who have never been married). There are also missing data due to the respondents' refusal to answer certain sensitive questions (e.g., about their income level). Another example is when the respondent has no opinion or insufficient knowledge to answer the question. The researcher should anticipate these problems and attempt to minimize them in the research design and data collection stages. However, they may still occur and the researcher must deal with the resulting missing data. When the missing data occur in a random pattern (see, next section), there are ways to alleviate the problem.

In certain instances, the missing data process can be identified and controlled by the researcher. In these cases, the missing data are termed *ignorable*. One example of ignorable missing data process is when the data are censored. Suppose that a researcher is interested in estimating the heights of the U.S. population based on the heights of the armed services recruits. The data are censored because the armed services have height restrictions. Therefore, the researcher has the task of estimating the heights of the entire population when it is known that certain individuals are not included in the sample. However, the researcher's knowledge of the missing data process allows for the use of specialized methods, such as event history analysis to accommodate censored data. For a more detailed discussion of ignorable data, readers are referred to Little and Rubin (1987).

2.2.2. *Patterns of missing data*

When observations are missing, there are two questions that the researcher must address. First, how much of the data are missing? Although there is no clear guideline about how much missing data is too much, Cohen and Cohen (1983) suggested that 5% or even 10% missing data on a particular variable is not large, but the seriousness of greater proportions is more ambiguous. Obviously, the usefulness of a variable with the majority of its scores missing may be suspect.

The second and most important question that a researcher must address is whether the pattern of missing observations is random or not. Little and Rubin (1987) distinguish between data that are *missing at random* (*MAR*) versus data that are *not missing at random* (*NMAR*). MAR means that the probability of a missing value on some variables is independent of the respondents' true status on that variable. In other words, respondents with missing observations differ only by chance from those who have scores on that variable. Therefore, results based on data from respondents with non-missing data should be generalizable to those with missing data.

On the other hand, when data are NMAR, there is a relationship between the variables with missing data and those for which the values are present. When data are NMAR, the nature of the pattern needs to be understood before one can interpret the results correctly (for more information about procedures to evaluate the randomness of patterns of missing observations, please see, the next section). It is important to note that if the missing data pattern is not random, then there is no statistical means to alleviate the problem. In fact, all techniques for dealing with missing observations described below assume that the pattern of data loss is random. However, none of these techniques can do anything about the potential bias in results based on analysis of non-missing data when the pattern is NMAR.

Finally, there is another pattern of missing observations that is called *missing completely at random* (*MCAR*). MCAR is actually just a stronger assumption about the randomness of the missing data compared to MAR. Like MAR, the notion of MCAR means that the process of missing data on some variable is unrelated to respondents' true status on that variable. However, MCAR also means that the presence or absence of scores on a variable is unrelated to subjects' scores on other variables in the data set. In contrast, MAR allows for this possibility.

The following example by Byrne (2001) provides an illustration of the different patterns of missing data. Let us suppose that in the demographics section of a questionnaire, respondents are asked to provide information both about their education level and income. Also, let us assume that all respondents answer the education question but not everyone answers the income question. The issue here is whether the missing data on income are MAR, MCAR or NMAR. If a respondent's answer to the income question is independent of both income and education, then the missing data can be regarded as MCAR. However, if those with higher education are more or less likely to reveal their income, but among people with the same level of education the probability of reporting income is unrelated to income, then the missing data are MAR. Finally, if even among people with the same level of education, those with high income are either more or less likely to report their income, the missing data are NMAR.

2.2.3. *Diagnosing the randomness of missing data*

As discussed in the previous section, it is important to investigate whether data are missing at random or not. According to Little and Rubin (1987), the following two methods are available for diagnosing the randomness of missing data. The first method assesses the missing data for a single variable by forming two groups: one with missing data for the variable and one with valid values of the variable. If patterns of significant differences are found between the two groups, on other variables of interest, it would indicate a non-random missing data process. The researcher should examine a number of variables to see whether any consistent pattern emerges. Although some differences will occur by chance, any series of differences may indicate an underlying pattern.

A second method is to assess the correlation of missing data for any pair of variables. For each variable, valid data are replaced by the value of one, while missing data are replaced by zero. The missing value indicators for each variable are then correlated and the correlations indicate the degree of association between the missing data on each variable pair. Low correlations indicate randomness in the pair of variables. Although no guidelines exist for identifying the level of correlation needed to indicate that the missing data are not random, statistical significance tests of the correlations provide a conservative estimate of the degree of randomness. If randomness is indicated for all variable pairs, then the analyst can assume that the missing data can be classified as MCAR. If significant correlations exist between some pairs of variables, then the analyst may have to assume that the data are only MAR.

2.3. Techniques for dealing with missing data

According to Kline (1998), there are three ways to treat missing data: (a) to delete them, (b) to replace (impute) the missing data with estimated scores and (c) to model the distribution of missing data and estimate them based on certain parameters. Each one of these families of techniques is discussed below.

2.3.1. Deletion procedures

2.3.1.1. Listwise deletion. This method eliminates from further analysis all cases with any missing data (see, Table 1). As a result, it sacrifices a large amount of data (Malhotra, 1987). According to Kim and Curry (1977), randomly deleting 10% of the data from each variable in a matrix of five variables can easily result in eliminating 59% of cases from analysis. Kaufman (1988) reports that he has seen a sample size drop from 624 to 201 using listwise deletion.

Despite the fact that the large loss of data reduces statistical power and accuracy (Little and Rubin, 1987), listwise deletion is the default option for analysis in most statistical software packages. On the other hand, it is worth mentioning that listwise deletion gives very conservative estimates of the parameters. Empirical researchers usually want to find significance to support their theory. Listwise deletion results in conservative results, since by reducing the sample size, it also results in a decrease in statistical power. Hence, it tends to make fewer variables statistically significant.

2.3.1.2. Pairwise deletion. Pairwise deletion deletes cases only from those statistical analyses that require the information. For example, if a respondent is missing information on variable A, the respondent's data could still be used to calculate other correlations, such as the one between variables B and C. Compared to listwise deletion, pairwise deletion preserves much more information that would have been lost if the researcher was using listwise deletion (Roth, 1994). The most important problem of pairwise deletion is related to the interpretation of covariance or correlation matrices. According to Kim and Curry (1977), since different parts of the sample are used for each statistic, the correlations or covariances may be biased (mathematically inconsistent). This in turn could have serious negative effects on maximum likelihood-based programs such as the structural equation modeling statistical packages (e.g., LISREL, EQS, AMOS, etc.).

Researchers should also be careful when using pairwise deletion in multiple-item scales with relatively low reliability (Roth et al., 1999). One of the key reasons why survey researchers use multiple-item scales is because scales enhance the reliability of the data. If a scale is reliable to begin with (e.g., it has a Cronbach's alpha of 0.90), then averaging fewer items (when one or more responses are missing) does not cause any major problem. However, if the Cronbach's alpha is marginal (about 0.60), then not using all the items in the scale because of missing data may result in an unreliable scale. Thus, pairwise deletion should be used only if a multiple-item scale is reliable to begin with.

Monte Carlo studies have shown that listwise deletion gives less accurate estimates of population parameters, such as correlations (Gleason and Staelin, 1975; Kim and Curry, 1977; Malhotra, 1987; Raymond, 1986; Raymond and Roberts, 1987) and regression weights (Kim and Curry, 1977; Raymond and Roberts, 1987). Pairwise deletion is consistently more accurate (Gleason and Staelin, 1975; Kim and Curry, 1977; Raymond, 1986), though the differences can sometimes be small (Raymond, 1986).

Table 1
Techniques for handling missing data

Technique	Description	When to be used	Advantages	Disadvantages	Studies
Deletion-based					
Listwise deletion	Eliminates from further analysis all cases with any missing data	Should be avoided	Easy to use (default in most statistical packages) "Conservative": hard to find statistical significance	Sacrifices a large amount of data and has a negative impact on statistical power	Kim and Curry (1977), Raymond (1986), Malhotra (1987), Little and Rubin (1987)
Pairwise deletion	Deletes cases only from those statistical analyses that require the information	When data are missing at random and less than 10% are missing, when reliability is high on a multi-item scale	Preserves more data and is more accurate than listwise deletion	Correlations or covariances may be biased	Gleason and Staelin (1975), Kim and Curry (1977), Raymond (1986), Roth (1994)
Replacement-based					
Mean substitution	Missing value is replaced by the mean (see, text below for variants)	When correlations between variables are low and less than 10% of the data are missing	Preserves the data and is easy to use	Negative impact on variance estimates and degrees of freedom	Ford (1976), Raymond (1986), Little and Rubin (1987), Kaufman (1988), Hawkins and Merriam (1991), Quinten and Raaijmakers (1999)
Total mean substitution	Missing value is replaced by the mean on the item for all respondents answering the question	When there are relatively low correlations ($r < \|.20\|$) between the missing variable and the other variables in the data	Easy to use (built-in in most statistical packages), sample retention	Downward biased variance/covariance estimates	Little and Rubin (1987), Quinten and Raaijmakers (1999)
Subgroup mean substitution	Missing value is replaced by the mean on the subgroup of which the respondent is a member	When it is easy to define subgroups	Gives better estimates, when compared to the total mean substitution procedure	Downward biased variance, arbitrary nature of defining subgroups in some situations	Ford (1976)
Case mean substitution	Missing value is replaced with the intraindividual mean of the respondent for all non-missing items	Particularly recommended for the construction of scale scores	Sample retention	Assumes equal means and standard deviations between predictors and missing variable	Nie et al. (1975), Raymond (1986)
Regression imputation	Estimates relationships among variables, and then uses coefficients to estimate the missing value	When more than 20% of the data are missing and variables are highly correlated	Estimated data preserve deviations from the mean and the shape of the distribution	Distorts the number of degrees of freedom and could artificially increase the relationships	Frane (1976), Cohen and Cohen (1983), Raymond and Roberts (1987), Little and Rubin (1987), Little (1988)

Table 1 (*Continued*)

Technique	Description	When to be used	Advantages	Disadvantages	Studies
Hot-deck imputation	Replaces a missing value with the actual score from a similar case in the dataset	When data are missing in certain patterns	Missing data are replaced by realistic values and not means that distort distributions	Little theoretical or empirical work to determine its accuracy, problematic if no other case is closely related in all aspects of the data set	Ford (1983), Roth et al. (1999)
Model-based					
Maximum likelihood	Parameters are estimated by available data and missing scores are estimated based on the parameters	When distributional assumptions are met	Increased accuracy if model is correct	The distributional assumptions required by the technique are relatively strict	Donner and Rosner (1982), DeSarbo et al. (1986), Lee and Chiu (1990)
Expected maximization	An iterative process that continues until there is convergence in the parameter estimates	When distributional assumptions are met	Increased accuracy if model is correct	The algorithm takes time to converge and is too complex	Laird (1988), Little and Rubin (1987), Malhotra (1987), Azen et al. (1989), Ruud (1991), Graham and Donaldson (1993)

2.3.2. *Replacement procedures*

Before discussing replacement procedures in more depth, it is important to note that empirical researchers should be careful before they start replacing data. Data replacement does not compensate for a badly designed instrument or for poor data collection. Overall, replacement procedures can be used in certain cases, as long as the researcher has a good reason for replacing (see, next paragraph and Table 1).

In general, the replacement procedures are easy to perform, and some are included as options in statistical packages. The most important advantages of these procedures are the retention of the sample size and, consequently, of statistical power in subsequent analyses. To a greater or lesser extent, all replacement procedures are biased if there is a non-random distribution of missing values. However, replacing missing data is appropriate when correlations between variables are low (Little and Rubin, 1987; Quinten and Raaijmakers, 1999). Also, the problem of having missing data affects Likert-type scales and replacement is suggested for the construction of scale scores (Quinten and Raaijmakers, 1999).

Many different missing data replacement procedures have been developed over the years. In general, it has been found that the differences between the various methods decrease with: (a) larger sample size, (b) a smaller percentage of missing values, (c) fewer missing variables and (d) a decrease in the level of the correlations between the variables (Raymond, 1986). However, Kromrey and Heines (1994) reported that this is not the case if the effects of the treatments on the analytical statistics are taken into account. With larger sample sizes, in fact, the differences between the various replacement procedures are found to increase; this provides further evidence that in assessing the effectiveness of missing data treatments, both the accuracy of estimating the value of missing data and the accuracy of estimating the statistical effects have to be considered.

Three types of replacement procedures can be distinguished: mean-based, regression-based and hot-deck imputation.

2.3.2.1. Mean substitution. There are three variants of mean substitution: total mean substitution, subgroup mean substitution and case mean substitution. Under total mean substitution, the missing value of a variable is replaced by the mean on the item for all respondents answering the question. According to the subgroup mean substitution, the missing value is replaced by the mean of the subgroup of which the respondent is a member. The third variant of mean substitution is the case mean substitution, which replaces missing values with the intraindividual mean of the respondent for all non-missing items.

Studies have been somewhat inconclusive regarding the effectiveness of mean substitution. Kim and Curry (1977) found mean substitution to be less accurate than listwise deletion in reproducing a correlation matrix, while others, have shown that mean substitution is more accurate than listwise and pairwise deletion (Chan and Dunn, 1972; Chan et al., 1976; Raymond and Roberts, 1987).

2.3.2.2. Regression imputation. This is a two-step approach: first, the researcher estimates the relationships among variables, and then uses the regression coefficients to estimate the missing value (Frane, 1976). The underlying assumption of regression imputation is the existence of a linear relationship between the predictors and the missing variable. The technique also assumes that values are missing at random (i.e., a missing value is not related to the value of the predictors).

2.3.2.3. Hot-deck imputation. According to this technique, the researcher should replace a missing value with the actual score from a similar case in the dataset. A number of highly visible surveys have adopted hot-deck strategies such as the British Census, the U.S. Bureau of the Census, Current Population Survey, the Canadian Census of Construction, the U.S. Annual Survey of Manufactures and the U.S. National Medical Care Utilization and Expenditure Survey (Roth et al., 1999).

2.3.3. Model-based procedures

2.3.3.1. Maximum likelihood. The maximum likelihood approach to analyzing missing data has many different forms. In its simplest form, it assumes that the observed data are a sample drawn from a multivariate normal distribution (DeSarbo et al., 1986). The parameters are estimated by available data, and then missing scores are estimated based on the parameters just estimated.

Contrary to the techniques discussed above, maximum likelihood procedures allow explicit modeling of missing data that is open to scientific analysis and critique. For more information on this approach, readers are referred to DeSarbo et al. (1986) or Lee and Chiu (1990).

2.3.3.2. Expectation maximization. The expectation maximization algorithm is an iterative process (Laird, 1988; Ruud, 1991). The first iteration estimates missing data and then parameters using maximum likelihood. The second iteration re-estimates the missing data based on the new parameter estimates and then recalculates the new parameters estimates based on actual and re-estimated missing data (Little and Rubin, 1987). The approach continues until there is convergence in the parameter estimates.

3. Treatment of missing data in operations management

We examined one hundred and three survey-based articles from the *Journal of Operations Management* (JOM) between 1993 and 2001. The treatment of missing data was evaluated by two raters. Each judge rated articles independently. When disagreements over coding arose, the raters exchanged coding sheets and discussed differences. Disagreements were settled by consensus.

Table 2 presents the results of our analysis. Several conclusions can be drawn from those results. First, 67% of the articles did not mention anything about whether there were missing data and, if there were, how they were treated. There are at least two possible explanations for this finding. On the one hand, experienced empirical researchers may see no need in "boring" their readers with so much detail. On the other hand, some authors may ignore the issue all together and never deal with it during their data analysis.

Second, authors are not explicit about their treatment of missing data. Only 4 out of 45 articles that were coded as having missing data have clearly stated the technique used (listwise deletion in all four cases). This required the coders to make a number of inferences. For example, the technique might be inferred by examining the total sample size of the study, examining the degrees of freedom in a given set

Table 2
Use of missing data techniques (MDT) in *Journal of Operations Management*

	Articles
Item non-response discussed	
Yes	34 (33)
No	69 (67)
Agreement between raters ($N = 103$) (%)	93.2
Method for arriving at MDT judgment	
MDT stated in article	4 (8.9)
MDT inferred(a)	41 (91.1)
Agreement between raters ($N = 45$) (%)	95.5
Missing data technique	
Listwise deletion	45 (100)
Other	0 (0)
Agreement between raters ($N = 45$) (%)	93.3
Sample size	
Average sample size	263.22
Average number of missing data	34.32
% of missing data	13.04

Values in parenthesis are percentages.

of analyses, and comparing the actual degrees of freedom with the expected number of degrees of freedom (Roth, 1994).

Third, in about half of the studies the authors used phrases such as "the analysis is based on 145 completed questionnaires", or "160 usable questionnaires were returned". These phrases can be interpreted in more than one ways; either there were no missing data (although most empirical researchers would agree that it is nearly impossible for any large-scale survey to not have missing data), or the authors used listwise deletion that eliminates cases with missing data and results in "complete" questionnaires. Overall, it seems that researchers do not always describe in detail the approach they have taken with regard to missing data. This could be attributed to various reasons. It is possible that experienced and well trained researchers simply use a procedure (most probably listwise or pairwise deletion), but do not report it. An alternative explanation is that authors with experience in publishing survey-based work might not provide any information on missing responses in order to avoid potential comments from reviewers who may give them a hard time over missing data.

Fourth, on average 13% of the data were missing. Such a high percentage of missing data could have catastrophic implications for statistical power. As demonstrated by Quinten and Raaijmakers (1999), 10% missing data could result in a 35% loss of statistical power.

The results also show that listwise deletion was the preferred technique in all instances. The potentially detrimental effects of listwise deletion are evident through the following example: In one study, the abstract states that the results are based on a sample size of 576 respondents but all analyses are conducted with a sample size of 275. In this particular instance, listwise deletion had resulted in a loss of 301 cases (more than 50% of the sample!). Overall, most advanced methods, such as imputation and model-based procedures, were never used, or, if they have been used, they have not been reported. Given the superiority of those methods under certain circumstances, it is discouraging that they have not been utilized. Guidelines for using the various techniques are discussed below.

4. Recommendations to operations management researchers

Table 3 provides guidelines on how to handle missing data. The two primary factors considered for the construction of Table 3 are the amount and the pattern of missing data. Prior research has shown that the selection of a certain missing data technique over others is less critical if the amount of missing data is small (Frane, 1976; Kaufman, 1988). Specifically, studies have shown that when less than 10% of the data are missing there is little difference in the parameter (Raymond and Roberts, 1987). The selection of a certain technique becomes more important as the amount of missing data approaches 20% of the data set (Raymond and Roberts, 1987) and extremely important when 30–40% of the data is missing (Malhotra, 1987). At this high level, different techniques can lead to very different results (Stumpf, 1978).

The second factor in Table 3 is the pattern of missing data; how and why the data are missing (see, Section 2.2). According to Little and Rubin (1987), the performance of any technique depends heavily on the mechanisms that lead to missing values.

In addition to the two factors described in the previous paragraphs, the recommendations of Table 3 are based on three more criteria: (a) statistical accuracy, (b) the time and effort required by the researcher and (c) the impact on statistical power. As a

Table 3
Suggested missing data techniques according to amount and pattern of missing data

Amount of missing data	Pattern		
	Missing completely at random	Missing at random	Non-missing at random
Less that 10%	1) Pairwise 2) Regression or hot-deck	1) Hot-deck 2) ML 3) Regression	1) ML 2) Hot-deck or regression
More than 10%	1) Pairwise 2) Regression or hot-deck	1) Hot-deck 2) ML	1) ML

Notes: (a) the preferred order of the missing data techniques is denoted by the number in front of each technique; (b) the above table is based on original work by Roth (1994).

result, we recommend easier to use techniques when the level of statistical accuracy appears to be similar and/or when missing data patterns ''allow'' such approaches. This explains the preference for hot-deck approaches over maximum likelihood or expectation maximization approaches under conditions such as missing at random data. Finally, techniques that preserve statistical power were chosen when accuracy and friendliness were similar. This explains the preference given to pairwise deletion when data are missing completely at random.

Overall, we recommend the following to OM researchers who are dealing with missing data. First, they should understand the reasons that lead to missing data and make an effort to avoid/minimize missing data. This can be achieved by using questionnaires that are easy to understand, training research assistants, rigorous follow-up to interviews or questionnaires, or even gathering additional independent and dependent variables that may be used to impute missing data (Roth, 1994). Technology can also play a role in minimizing missing data. As shown by two recent studies (Boyer et al., 2002; Klassen and Jacobs, 2001), electronic (web-based) surveys have fewer missing responses than print surveys. The issue can also be dealt with by paying more attention to procedural issues such as errors in data entry (Flynn et al., 1990). In addition, researchers may wish to consider re-sampling the cases with missing data (Graham and Donaldson, 1993). While this requires some extra effort, it enables the researcher to study the relationship of various types of gathered data to missing data.

Second, researchers should not always fall for listwise deletion that provides a ''quick and easy fix''. Despite the fact that listwise deletion is a ''conservative'' technique that results in researchers ''making it harder for themselves'' (see, Section 2.3.1), it also reduces statistical power and accuracy more than many other techniques. Instead, researchers should consider the recommendations of Table 3.

Finally, authors should be very explicit about how they handle missing data in their manuscripts (method used, why, etc.). It is understandable that experienced and well trained empirical researchers take most of these issues for granted but they should try to keep a balance between not boring the reader with every minor task and providing the information necessary for the reader to understand and evaluate the analysis. This information is of paramount importance, since not only it allows others to better understand the analysis but it also enables the replication of previous studies.

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