Treatment and reporting of item-level missing data in social science research

Most quantitative studies in the social sciences suffer from missing data. However, despite the large availability of documents and software to treat such data, it appears that many social scientists do not apply good practices regarding missing data. We analyzed quantitative papers published in 2017 in six top-level social science journals. Item-level missing data was found in at least 69.5% of the papers, but their presence was explicitly reported in only 44.4% of all analyzed papers. Moreover, in the majority of cases, the treatments applied to missing data were incorrect, with many uses of deletion methods that are known to produce biased results and to reduce statistical power. The impact of missing data and of their treatment on results was barely discussed. Results show that social scientists underestimate the impact of missing data on their research and that they should pay more attention to the way such data are treated.

Keywords: missing data; reporting practices; complete case analysis; pairwise deletion; imputation

Introduction

In quantitative research, missing data (MD) are considered the rule, not the exception (Molenberghs, Fitzmaurice, Kenward, Tsiatis, & Verbeke, 2014), and this applies to the social sciences as much as any other scientific discipline. However, the reporting of MD in scientific publications and the ways in which such data are treated are often less than clear, if mentioned at all. This is a pernicious threat to the quality of research, and the social sciences cannot do without accurate missing data treatments especially if social scientists want their results to be considered as robust as those of more fundamental fields, such as biology or physics, and if they want to fight on equal terms to obtain funding (Todd, 2014).

The purpose of this paper is not to add one more publication to the existing literature regarding the causes and consequences of MD. Numerous documents are available to researchers for that purpose, either at an introductory level (e.g., Allison, 2001; McKnight, McKnight, Sidani, & Figueredo, 2007) or at a more technical level (e.g., Dong & Peng, 2013; Molenberghs et al., 2014). Our objective is to determine whether scientific publications in the social sciences currently apply good practices for handling and reporting missing data. This study's results should be beneficial to all researchers dealing with quantitative data by helping them compare their own practices with those of researchers from the same field and by reporting possible improvements to reach higher standards.

Before presenting our methods and results, some basic information is required for our research to be understood correctly. MD are classically classified into three broad categories (Rubin, 1976): missing completely at random (MCAR: the missing information does not depend either on missing values or on other variables), missing at random (MAR: the missing information depends on other variables only), and missing not at random (MNAR: the missing information depends, at least partially, on the missing values themselves). When the main consequence of MCAR data is a reduced sample size, the two other MD mechanisms add a high risk for biased point estimates and underestimation of variances, leading to incorrect inferences. MCAR is very rare in practice, but, as will be seen later, many researchers still rely on listwise deletion, a method that can be considered correct *only* in the MCAR situation.

Another useful distinction is between unit- and item-level MD. We speak of unit-level MD when all information regarding a case or a subject is missing. In cross-sectional studies, this happens when a subject who was included in the sample does not provide any information, either because he/she refuses to answer or because he/she was not contacted at all. In longitudinal studies, when a subject quits a study at some point in time (causing attrition), he/she produces unit-level MD for all subsequent waves of the study. By contrast, we speak of item-level MD (ILMD) when only some part of the information is missing for a given subject. This occurs, for instance, when a subject does not want to answer sensitive questions regarding sexuality or substance consumption but answers all other questions. Even though these two types of MD are related, they imply different challenges for the researcher, with potentially different answers. While MD always imply a reduced sample size and increased risk of bias and inference errors, at the unit level, the main threat concerns the representativeness of the whole sample, whereas at the item level, the threat has more to do with the comparability and compatibility of all of the study's results. Consider, for instance, two continuous variables: age and income. Suppose that we have complete data for age but that the probability of MD on income increases linearly with the income level. If we then compute summary statistics using all the available data for the two variables, the results will not be comparable because they will be computed on two different samples. Moreover, if a correlation is computed between the two variables, this correlation will concern only those respondents who have answered to both variables, and since the MD on income are not MCAR, the resulting correlation will be biased.

Remedies to item-level missing data can be broadly classified into three categories:

- **Deletion methods,** including listwise deletion (also known as complete case analysis: all cases with at least one missing datum are removed from all analyses) and pairwise deletion (also known as available case analysis: each analysis uses all cases without MD on the variables necessary for this specific analysis).
- **Imputation**, that is, replacement of the MD by one (single imputation) or several (multiple imputation) likely values that can be computed from different

statistical models, ranging from an average of observed values to complex regression models (e.g., Lee et al., 2016).

- **Maximum likelihood methods** that estimate the true value of the parameters of interest from the likelihood of the model under a set of hypotheses regarding the data distribution but without imputing missing values (e.g., Enders, 2009).

A fourth approach, weighting of the observed cases, can also be used, but this is more appropriate for cases of unit-level MD.

To the best of our knowledge, only a few papers have tried to describe systematically how MD are reported in the scientific literature. Eekhout, de Boer, Twisk, de Vet, and Heymans (2012) explored the reporting practice in epidemiology; Rombach, Rivero-Arias, Gray, Jenkinson, and Burke (2016) considered the case of patient-reported outcomes; Karahalios, Baglietto, Carlin, English, and Simpson (2012) were interested in cohort studies with multiple assessments of outcome; Wood, White, and Thompson (2004), Fielding, Maclennan, Cook, and Ramsay (2008), Deo, Schmid, Earley, Lau, and Uhlig (2011), Bell, Fiero, Horton, and Hsu (2014), Powney, Williamson, Kirkham, and Kolamunnage-Dona (2014), and Akl et al. (2015) considered randomized trials; Masconi, Matsha, Echouffo-Tcheugui, Erasmus, and Kengne (2015) considered studies about type 2 diabetes mellitus; and Hussain et al. (2017) considered palliative care trials. However, no study to date has really considered the field of social sciences specifically. This constitutes a gap, since research practices, including data collection and statistical analyses, vary much across fields, with data more or less prone to missingness and analytical techniques more or less affected by MD. Moreover, there is often a link between the MD treatment method and the final statistical model of data analysis. For instance, when imputation is used, each statistical approach can require a different imputation model, as shown, for example, by Farhangfar, Kurgan, and Dy (2008) in the case of classification algorithms.

In this paper, we focused on ILMD only. Our goals were 1) to describe how such data are currently reported in the social science literature, and 2) to understand the current practices regarding the treatments applied to such data. The rest of the paper is organized as follows: We begin by describing the selection process of scientific publications that were included in our study. We then present descriptive statistics of the way ILMD are treated and reported. Lastly, we discuss our findings, establishing a relationship between the treatment and reporting of missing data and the inherent constraints of data as well as the specific characteristics of scientific publishing. Minimal guidelines for reporting missing data reporting are also provided.

Data and methods

We selected six top-ranked journals in social sciences: *American Journal of Sociology*, *Social Politics*, *Gender & Society*, *Demography*, *American Journal of Political Science*, and *Educational Researcher*. Our decision to include these journals was based on three considerations: First, they had to cover different disciplines of the social sciences. Second, they had to have high impact factors (compared to other journals from the same discipline), that is, they could be considered as influential. Finally, they had to publish quantitative studies on a regular basis. Of course, because some disciplines produce more qualitative than quantitative research, the third point was more difficult for gender studies than demography, for instance. Given the high pressure placed on scientists to publish in highly ranked, prestigious journals, those that had the abovementioned characteristics were expected to receive multiple submissions and be able to choose to publish only the very best ones that used the highest methodological standards.

All research papers published in 2017 in the selected journals were then considered for inclusion in our study.[1] As a first step, all papers were screened, and papers without substantive quantitative analyses were excluded (see Figure 1). The remaining papers were then analyzed (including annexes, supplementary material, statistical codes, and links to external files when available), and information regarding the reporting of ILMD and the treatments applied to these data was extracted (see Tables 1 and 2 for details of the extracted data). Then, this information was used to summarize the type of treatments that were generally applied for item-level missing data, as well as the way such data and treatments were reported in social science journals.

Results

Figure 1 describes the inclusion of research papers in our study. Globally, 151 out of 230 screened papers (65.7%) were included. Seventy-nine papers were excluded, either because they were presenting purely qualitative analyses or because they were mainly theoretical, without substantive quantitative analyses.

[1] Given the large number of quantitative research papers published each year in *Demography*, we chose to consider only issues 1, 3, and 5 from 2017.

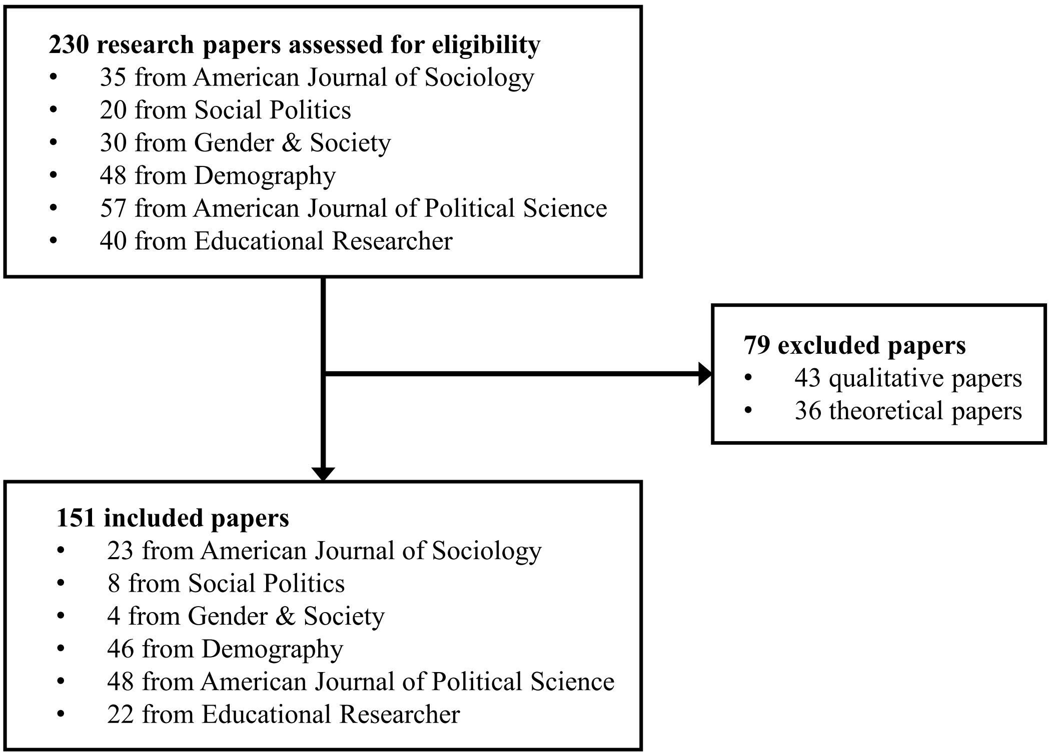

Figure 1: Inclusion of research papers.

Tables 1 and 2 summarize our main findings. From Table 1, we can see that the majority of studies relied on datasets with MD, but they were not always reported as such. In 38 cases, ILMD were not explicitly mentioned, but their presence can be deduced from variations in the information provided (number of data reported in each table and number of degrees of freedom). In 46 cases, no indication of the presence of ILMD was found, but this is not proof that such data were not present in the data; it only indicates that we were unable to demonstrate the presence of ILMD from the elements reported in the paper. In the case of secondary data, ILMD were more often reported than in the case of primary data. This may be because scientists collecting their own primary data pay more attention to their quality or because cases with missing information are suppressed at a very early stage of the data collection process. For instance, when building a dataset by combining information from different administrative sources, it is easy to take into account only those subjects for whom complete information can be found, discarding incomplete cases. This is not good practice, of course, because it generally leads to a non-representative sample, but it could be considered as an option by some researchers, since it would simplify data analysis.

Table 1: Relationship between the source of data and the reporting of ILMD.

	Source of data		
Presence of ILMD	Primary	Secondary	Total
Yes, explicitly reported	14 (25.0%)	53 (55.8%)	67 (44.4%)
Yes, deduced from reading	21 (37.5%)	17 (17.9%)	38 (25.2%)
No	21 (37.5%)	25 (26.3%)	46 (30.5%)
Total	56	95	151

Table 2 describes the information provided about ILMD (only for papers explicitly reporting ILMD) and how the data are treated (for all papers with ILMD). First, even if ILMD are acknowledged in the paper, the reasons for these MD are rarely detailed (15 times in 67 papers). Similarly, the number of ILMD was reported in less than half of the papers, and often only globally, either by a percentage or the total number of incomplete cases. Complete and incomplete data were rarely compared for significant differences (7 papers), and the type of MD (MCAR, MAR, or MNAR) was never checked, with one paper (wrongly) assuming MCAR and another assuming MAR.

Table 2: Reporting and treatment of ILMD in social science research papers.

	Presence of ILMD	
	Yes, explicitly reported (n=67)	**Yes, deduced from reading (n=38)**
Reason for ILMD indicated (at least partially)?		
Yes	15 (22.4%)	
No	52 (77.6%)	
Number of ILMD reported?		
Yes, globally	21 (31.3%)	
Yes, by variable	10 (14.9%)	
No	36 (53.7%)	
Comparison of complete and incomplete data?		
Yes	7 (10.4%)	
No	60 (89.6%)	
Type of MD explored?		
Yes	0 (0%)	
No	67 (100%)	
Method of ILMD treatment reported?		
Yes	56 (83.6%)	
No	11 (16.4%)	
Method of treatment applied to ILMD*		
Listwise deletion	29 (32.2%)	4 (10.5%)
Pairwise deletion	18 (20.0%)	34 (89.5%)
Simple imputation	19 (21.1%)	0 (0%)
Multiple imputation	14 (15.6%)	0 (0%)
Maximum likelihood	0 (0%)	0 (0%)
Other (weighting, propensity score, ad hoc)	10 (11.1%)	0 (0%)
In case of imputation, sensitivity analysis or other comparison of data before and after imputation?**		
Yes	4 (13.3%)	
No	26 (86.7%)	
Impact of ILMD on results discussed?		
Yes	6 (9.0%)	
No	61 (91.0%)	

* For treatment methods applied to MD, the total is larger than the number of papers because several methods were sometimes jointly used.

** Imputation was mentioned in 30 papers.

Of the 67 papers explicitly indicating the presence of ILMD, the majority (56) also gave information about the treatment method. For the remaining 11 papers, as well as for the 34 papers that did not explicitly report their MD, the treatment method was identified through a careful reading of the papers. In the latter category of papers, pairwise deletion was used in 30 out of 34 cases, the 4 remaining cases using listwise deletion. On the other hand, among papers in the first category, imputation was mentioned about half the time, with pairwise and listwise deletion being the other family of treatment used. Note that we classified under "simple imputation" all methods replacing MD by a single value, so this category includes methods as different as mean and median imputation, last observation carried forward, linear interpolation, and regression. No paper made use of maximum likelihood methods. Finally, specific or ad hoc methods were used in 10 papers but without demonstration of the merits of the chosen method.

When imputation was used, only 4 out of 30 papers applied a form of sensitivity analysis regarding the imputed values. More generally, only 6 out of 67 papers discussed the possible impact of the MD on the statistical results.

Discussion

In the social sciences, data are often supposed to be representative of a specific population, and the researcher wants to be able to draw conclusions concerning this population of interest. Even if data collection was conducted in the appropriate manner and unit-level MD were correctly handled through proper weighting, ILMD are nonetheless likely and have to be treated properly. This is even more important because social science data about people living in the real world are generally difficult to collect and less precise than in other fields. Therefore, everything must be done to ensure the highest possible quality of these data.

The fact that many journals allow for supplementary material is good because it can be used to provide more details about the data, models, and statistical procedures. However, it is not a good practice to put all information about MD in supplementary material because most readers will not look at it. Basic information about MD must be provided in the main article, and if no missing data are present at all, this should be stated explicitly. During our analysis of research papers, we came across different wording used to speak about missing information. In addition to "missing data," expressions such as "non-available information" or "we could not locate sufficient information" were also used. Such wording should be avoided because it tends to hide or minimize the reality of the MD.

Some studies used sophisticated statistical techniques, such as instrumental variables (IV), multi-level models, and structural equation models, but at the same time they still relied on very basic MD treatments. This gap between data treatment and analysis method is most intriguing because one of the most basic rules taught in almost all introductory-level methodological lectures is that the quality of the end results cannot be better than the quality of the raw data. As noted by Dale (2007), social science researchers can be reluctant to adopt full and sometimes complicated MD treatments, but the evidence indicates that 1) social scientists must be better educated about the correct use of all kind of methods, 2) all researchers should master the tools they use, and 3) working in a multidisciplinary team that includes someone with methodological expertise is a good way to accomplish high-level research and publications.

It could be argued that when a study is based on a convenience sample or when it does not require a representative sample, losing additional cases because of ILMD is of no importance. We do not accept this argument because 1) MD always imply a smaller sample size and thus diminished statistical power; 2) all results of a study should be obtained from the same sample in order to achieve coherence, which is not the case when pairwise deletion is used; and 3) ILMD are rarely MCAR, so that each additional missing datum may imply a reinforced tendency to accept or reject a given hypothesis incorrectly, without a valid reason.

Our study indicates that the most used methods to treat ILMD are still deletion methods (listwise or pairwise), but even in the case of MCAR, these methods are not considered perfect (Pigott, 2010). On the other hand, only a minority of papers relied on imputation, and mostly on simple imputation rather than on the much better multiple imputation approach. Finally, no paper relied on the other family of methods regarded as appropriate for the treatment of MD, namely, maximum likelihood approaches. Thus, with a few exceptions, even when a better method than deletion was used, it was generally applied in a very crude way, without considering methods that are more sophisticated and accurate. It is also striking to note that the consequences for the final results of both MD and the treatments applied to these data were seldom discussed, even though there is much evidence in the literature that decisions taken about missing data can have an important impact on statistical results, and therefore on conclusions (e.g., Scheel et al., 2005; Berchtold & Surís, 2017).

Several sets of rules have been proposed for reporting the results of scientific research such as the STROBE statement (Elm et al., 2007; STROBE Statement website) or the QUORUM statement (Moher et al., 1999). These initiatives indicate the need to describe and report MD properly, but as noted by Masconi et al. (2015), complete guidelines for the correct reporting of MD are not yet available, with the exception of the proposal of Akl et al. (2015). We consider that a minimal description of missing data should include the three following aspects:

(1) **MD should be explicitly reported.** The number of MD should be given, the reasons for missing data should be explored, and the type of missing data should be determined (MCAR, MAR, MNAR). These features are essential to the ability to select the appropriate treatment for MD.

(2) **Treatments applied to MD should be accurately described.** Each method applied for minimizing the number or the impact of MD should be reported, along with the rationale for choosing this method rather than possible alternatives.

(3) **The impact of missingness on final results should be evaluated**. This step comprises the impact of both the MD and treatments applied to the missing data. There should be a comparison of complete and incomplete cases and a sensitivity analysis regarding imputed values (if any).

These elements do not guarantee that the MD have been correctly processed, but they provide sufficient information for the reader of a scientific publication to understand and judge the relevance of the treatments applied to the missing information.

Conclusion

The purpose of this study was to understand the current practices in reporting ILMD in scientific social science publications. Even if the results are not worse than those obtained in other scientific fields, they are nevertheless disappointing. Given the high number of available publications concerning various aspects of MD, and given the availability of treatment procedures in all major statistical software programs, the reliance in the majority of papers on problematic methods, such as listwise or pairwise deletion, gives cause for concern about the overall quality of published results. Note that there is a very significant difference between social science studies and experimental studies such as those conducted in psychology. In the latter case, studies can be replicated; therefore, errors due to mishandling of missing data can come to light later. In contrast, social data collected from the real-world population cannot be replicated; therefore, errors caused by missing data are more difficult to identify and thus more problematic.

Our study has at least two limitations. First, we considered publications from only six scientific journals, and our sample cannot be considered representative of all the quantitative social science literature, either in terms of size or diversity. However, our purpose was to identify the general current practices, and we do not believe that a larger sample would have entirely changed our results. Second, the decision to consider only ILMD might be queried, but we consider it a natural choice because many social science studies rely on secondary data, and in such cases full information about the sampling plan is sometimes difficult to obtain, or the treatment of unit-level MD has already been carried out or imposed by the maintainers of the dataset. By contrast, in the presence of ILMD, all end users have the same capacity to treat them correctly. Similarly, we did not consider the possible non-representativeness of samples, but this is beyond the scope of the present research.

Given the abovementioned limitations, additional studies are required. First, as social sciences is a very diverse field (with disciplines ranging from political science to gender studies), it would be helpful to compare the treatment and reporting of missing data between disciplines. However, even using a larger sample than those used in previous studies was not sufficient to allow for such comparisons without taking an extremely high risk of obtaining false-positive results. Moreover, multiple journals should be analyzed from each discipline to avoid results that are influenced by specific journal guidelines. Second, the treatment and reporting of unit-level missing data should be considered. As explained previously, we chose to not consider this type of data in our study; however, it could be the subject of another study. Finally, the relationship between the data collection method and missing data could be further analyzed.

To summarize, even if many social scientists are clearly aware of the problems linked to MD, the next step — correctly handling such data in research — is not being taken. A combination of reasons may explain this, including a lack of clear guidelines, the difficulty of using some methods, and the lack of space to discuss these issues in publications. However, since MD have the potential to change the end results of a study completely, they are not a minor aspect of scientific research, and they have to be taken very seriously. The social sciences must be aware of this, and the highest standard of MD treatment should be actively promoted. For researchers, this requires systematically asking for help from data collection and processing specialists. On the part of the editors of scientific journals, this implies paying attention not only to statistical analyses but also to all phases of data pre-processing, including the correct handling of missing data.

Disclosure statement

No potential conflict of interest was reported by the author.

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