**Understanding Missing Data in Meta-Analyses: A Tutorial and Discussion**

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Meta-analysis provides a unique lens through which to view the effectiveness of alcohol dependence interventions, particularly with tools like meta-regression and ANOVA models (see Cooper et al., 2019). But while the statistical methods for conducting meta-analysis have long been studied, there is little guidance on how best to handle the all-too-common scenario where data are missing from a meta-analysis (Pigott, 2001; Pigott, 2019). Moreover, discussion of missing data and how to deal with it depend on technical and often untestable assumptions (Little & Rubin, 2002; Pigott, 2001, 2019; Rubin, 1987; van Burren, 2012). In this tutorial, we provide an introduction to the terminology of missing data and demonstrate tools for examining and diagnosing potential issues using data on adolescent substance abuse interventions (Tanner-Smith et al., 2016).

**Data.** To demonstrate approaches to examining and diagnosing missingness, we use data on substance abuse interventions for adolescents (Tanner-Smith et al., 2016). These data comprise 328 distinct effects of substance abuse interventions on future substance use. These effects arise from 46 studies, and include information about estimated treatment effects and variances, as well as over three dozen variables describing how and where the intervention was implemented. While none of the effect estimates are missing, there is missingness on some 18 other variables of interest, including the sample composition of studies and the duration and intensity of the intervention.

**Visualization and summaries of missingness.** Any question of what to do about missing data starts with understanding how much of the data are missing and why (Little & Rubin, 2002; Rubin, 1987). These ideas are technical and not always widely known. Indeed, recent research has argued that MAR and MCAR are often misinterpreted as missing always at random (MAAR), which is a stronger assumption (Mealli & Rubin, 2015). Further, while there are a variety of metrics in use for quantifying and visualizing missingness in datasets outside of meta-analysis, including marginal rates of observation (i.e., response rates for each variable; see van Burren, 2012), such methods can provide an incomplete assessment of missingness in a meta-analysis. This is because not all studies carry the same weight in a meta-analysis; larger studies tend to be given greater weight than smaller studies in meta-analyses, and thus it may be *more* detrimental to the analysis when a larger study is missing data than when a smaller one is (see Cooper et al., 2019).

To that end, we discuss and demonstrate methods to plot missing data patterns and describe them numerically. We use and extend R’s naniar package to demonstrate how visualizations typically used with datasets outside of meta-analysis can be adapted to the realities of meta-analytic data (Tierney, 2019). We also show how some standard methods for quantifying missingness can be improved by incorporating different aspects of the standard meta-analysis and meta-regression models, including the precision with which effects are estimated.

**Description and assessment of assumptions.** Part of what makes missing data so tricky is that precisely how one should handle it will depend on why the data are missing, referred to as the *missingness mechanism*. There are generally three types of missingness types discussed in the literature: missing *completely* at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Potential corrections, and their accuracy, will be different depending on what type of missingness one encounters in their data (see Murray, 2018).

In the tutorial, we discuss that these notions are actually assumptions of the data, which has two important implications. First, assumptions of MNAR are not testable, but assumptions of MCAR are, and we demonstrate how to conduct such tests (Little, 1988). Second, we echo recent research that has argued that MAR and MCAR are often misinterpreted as referring to a mechanism *always* produces missing data, an idea called missing always at random (MAAR) (Mealli & Rubin, 2015). MAAR is a stronger assumption that MAR, but it is one that frequently aligns with discussion of missing data. Diagnostics to help identify MAAR have recently been proposed and we demonstrate methods for carrying out those diagnostics (Bojinov, in press).

**Potential corrections.** Given a thorough understanding about what data are missing and some idea of why, the next step is figuring out which statistical methods are appropriate for adjusting or contextualizing analyses. In other fields and for other statistical models, the effectiveness and implementation of methods such as multiple imputation (MI) or full information maximum likelihood (FIML) have been thoroughly studied (see Rubin, 1987; van Burren, 2012). However, ongoing research has demonstrated that the effectiveness of such methods must take into account various aspects of the data and model (Graham, 2009; Murray & Reiter, 2016). As of this writing, there has been little research on how appropriate existing methods and software are for dealing with missing data in meta-analyses, and ongoing research has argued that simply applying methods such as MI as one would with, say, a standard linear regression model can lead to bias (Schauer, 2019). Thus, we discuss potential corrections and identify areas where additional research is needed before the wider use of such corrections is warranted.

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