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Design approaches to experimental mediation☆

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ABSTRACT

Identifying causal mechanisms has become a cornerstone of experimental social psychology, and editors in top social psychology journals champion the use of mediation methods, particularly innovative ones when possible (e.g. Halberstadt, 2010, Smith, 2012). Commonly, studies in experimental social psychology randomly assign participants to levels of the independent variable and measure the mediating and dependent variables, and the mediator is assumed to causally affect the dependent variable. However, participants are not randomly assigned to levels of the mediating variable(s), i.e., the relationship between the mediating and dependent variables is correlational. Although researchers likely know that correlational studies pose a risk of confounding, this problem seems forgotten when thinking about experimental designs randomly assigning participants to levels of the independent variable and measuring the mediator (i.e., "measurement-of-mediation" designs). Experimentally manipulating the mediator provides an approach to solving these problems, yet these methods contain their own set of challenges (e.g., Bullock, Green, & Ha, 2010). We describe types of experimental manipulations targeting the mediator (manipulations demonstrating a causal effect of the mediator on the dependent variable and manipulations targeting the strength of the causal effect of the mediator) and types of experimental designs (double randomization, concurrent double randomization, and parallel), provide published examples of the designs, and discuss the strengths and challenges of each design. Therefore, the goals of this paper include providing a practical guide to manipulation-of-mediator designs in light of their challenges and encouraging researchers to use more rigorous approaches to mediation because manipulation-of-mediator designs strengthen the ability to infer causality of the mediating variable on the dependent variable.

Journal editors almost require mediation for publication, as noted by past Associate Editor of the *Journal of Personality and Social Psychology* (*JPSP*), Robert Cialdini (2009): "who could argue the importance of understanding what mediates the effects of interest to psychologists? Mediation is about what research psychologists care about—locating causality—and sophisticated psychometric techniques now allow meditational accounts of our major findings…" (p. 5). Associate Editor of *Journal of Experimental Social Psychology*, Jamin Halberstadt (2010) stated in a *Society for Personality and Social Psychology* electronic mailing list email that he outright rejects manuscripts that fail to examine mediation: "I will desk reject all papers that are unlikely to survive the review process, or do not on their face satisfy the standards or goals of the Journal. This includes, in my opinion, […] studies with no insight into psychological mechanism." Furthermore, in his editorial as incoming editor of *JPSP*, Eliot Smith (2012) identified mediation as a critical component of social psychology: An "explanation of observed effects in terms of underlying processes is almost a signature of articles that *JPSP* has historically published. Only rare articles demonstrate an effect without making at least some progress toward identifying the contributing processes. The most common approach to identifying those processes is mediation analysis. Thus recent developments in both the theory and the methods of mediation analysis are particularly significant for this journal" (p. 1–2).

Indeed, identifying causal mechanisms lies as a cornerstone of experimental social psychology. Many articles in top social psychology journals include mediation in at least one study: 59% of articles in *JPSP* and 65% in *Personality and Social Psychology Bulletin* (*PSPB*) from 2005 to 2009 (Rucker, Preacher, Tormala, & Petty, 2011); 41% of studies in *PSPB* within a six month period in 2007 (Kashy, Donnellan, Ackerman, & Russell, 2009); and 16% of studies in *Psychological Science* from 2011 to 2012 (Hayes & Scharkow, 2013).

In typical experimental designs examining mediation, researchers randomly assign participants to levels of the independent variable (X) and measure the mediating (M) and dependent (Y) variables—known

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as *measurement-of-mediation* designs (Spencer, Zanna, & Fong, 2005). (For clarity, we use M to reflect the *measured* mediator and M* to reflect the *manipulated* mediator). Researchers then perform statistical analyses to provide estimates for the models summarized in Fig. 1. Three regression equations comprise the single mediator model (shown in Fig. 1):

$$M = i_1 + aX + e_1 \quad (1)$$

$$Y = i_2 + cX + e_2 \quad (2)$$

$$Y = i_3 + c'X + bM + hXM + e_3 \quad (3)$$

where X is the independent variable, M is the measured mediator, and Y is the dependent variable; i_1, i_2, and i_3 are the intercepts in each equation; and e_1, e_2, and e_3 are the residual errors reflecting misprediction and unobserved omitted influences. Eq. (1) regresses M on X and *a* represents the statistical effect of X on M. Eq. (2) regresses Y on X and *c* represents the statistical effect of X on Y, or the total effect. Eq. (3) regresses Y on X and M simultaneously; c' represents the statistical effect of X on Y, adjusting for M, or the direct effect of X (i.e., the effect of X not mediated by M); *b* represents the statistical effect of M on Y adjusting for X; and *h* represents the statistical interaction effect of X and M but this is often assumed to be zero. The quantity, *ab*, is the estimator of the mediated effect (also called the indirect effect), if a series of assumptions are met.

Inferring that M mediates the relationship between X and Y rests upon the following assumptions: (1) no confounding of the X to Y relation; (2) no confounding of the X to M relation; (3) no confounding of the M to Y relation; and (4) no effects of X that confound the M to Y relation (VanderWeele & Vansteelandt, 2009). Furthermore, the temporal order of the variables X to M to Y is assumed correct and X, M, and Y are assumed reliable and valid measures of the intended constructs (MacKinnon, 2008).

Baron and Kenny's (1986) causal steps approach to mediation article is the most widely cited article in *JPSP* (Quinones-Vidal, Lopez-Garcia, Penaranda-Ortega, & Tortosa-Gil, 2004) at 20,326 times, according to Web of Science in June 2013. This suggests a reliance upon designs in which researchers measure the mediator and perform statistical mediation analyses (called *measurement-of-mediation designs* by Spencer et al., 2005)—particularly the causal steps approach—to provide evidence of a mediation relationship, over designs that randomly assign participants to levels of the proposed mediator, which we term *manipulation-of-mediator* designs (e.g., Smith, 2012). Measurement-of-mediation designs contain serious limitations (see for instance, Jacoby & Sassenberg, 2011; Spencer et al., 2005; and Stone-Romero & Rosopa, 2008); we focus our discussion on their limitations to causal inference of the M to Y relationship.

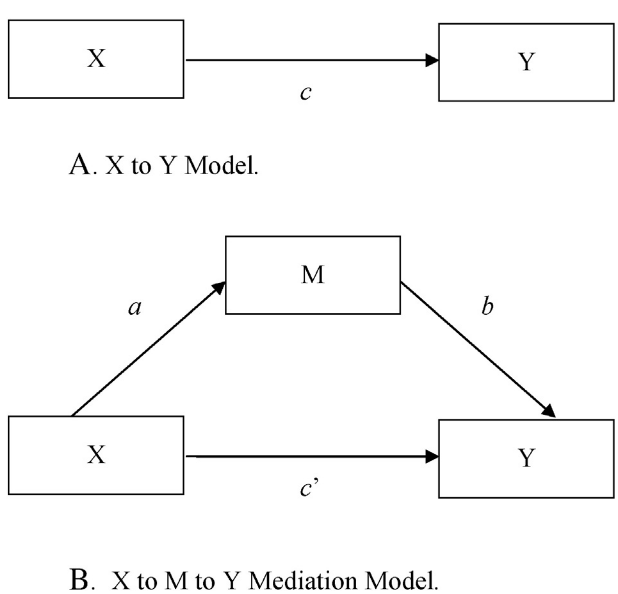

Fig. 1. Single mediator model in which X is randomized and M and Y are measured. The *a* coefficient reflects the effect of X on M; the *b* coefficient reflects the statistical effect of M on Y, controlling for X; the *c* coefficient reflects the total effect of X on Y, not controlling for M; and the c' represents the direct effect of X on Y, controlling for M.

The mediation model is a theoretical model implying causality: The independent variable causes a change in the mediator that causes a change in the dependent variable. According to Shadish, Cook, and Campbell (2002), three requirements exist to infer that one variable causes another. First, temporal precedence, such that the causal variable precedes the dependent variable in time. Second, covariation between the hypothesized causal and dependent variables, such that the independent and dependent variables vary together. Third, no plausible alternative explanations account for the relation between the hypothesized causal and outcome variables. Other approaches to causal inference exist that share some requirements of those outlined by Shadish et al. (2002), e.g., considerations for causal relations, Hill (1971), the potential outcomes model (Holland, 1988; Rubin, 1974, 1977), and related causal inference models (Pearl, 2000; Robins & Greenland, 1992) but the work by Shadish et al. (2002) remains widely used in social psychology. Therefore, we rely upon the classic Campbellian approach to causal inference (West & Thoemmes, 2010), which focuses upon a pattern of research results logically consistent with a research hypothesis.

Only well-designed experiments satisfy all three criteria of temporal precedence, covariation, and lack of alternative explanations: Researchers randomly assign participants to levels of the independent variable and significant differences between conditions on the dependent variable suggest the independent variable caused change in the dependent variable. The manipulation of the independent variable occurs before measurement of the dependent variable, which satisfies the temporal precedence criterion. An effect of the independent variable on the dependent variable satisfies the covariation criterion. Finally, random assignment to conditions ensures that no pre-existing individual differences between conditions account for the differences between conditions. Assuming no confounds exist between conditions, no alternative explanations should account for the pattern of findings. Thus, in a study examining the effects of X on Y, an experiment satisfies the causal inference criteria, therefore enabling the causal inference of X on Y.

A mediation model, however, is a more complicated model containing three causal paths—the effects of X on M, X on Y, and M on Y. In common social psychology experiments including mediation, researchers randomly assign participants to levels of the independent variable, measure the mediator and dependent variables, and perform statistical mediation analyses to demonstrate the ability of the mediator to *statistically* account for relationship between X and Y as shown in Fig. 1. However, providing *statistical evidence* of a mediation relationship fails to provide *causal evidence* of the mediation relationship. Random assignment of participants to levels of the independent variable enables causal interpretation of the X to M and X to Y relationships as it satisfies all three criteria for causal inference—temporal precedence, covariation, and the elimination of alternative explanations. Although measuring M and Y satisfies the criterion for covariation between M and Y, it does not demonstrate temporal precedence of M to Y or the elimination of alternative explanations for the relationship between M and Y. This design cannot differentiate whether M causes Y, Y causes M, or some unmeasured confounding variable causes M and Y. Due to lack of random assignment to levels of the mediator, claims regarding the causal relation of M to Y are unjustified. Participants self-select to levels of the mediator; their values of the mediator are not randomly assigned. Other variables could confound the relationship between M and Y if not included in the statistical analysis. These omitted variables provide alternative explanations for the relation between M and Y instead of

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