Statistical Mediation Analysis in Social Psychology: An Overview and Application of the Single Mediator Model

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Abstract

Mediation has become a prevalent statistical analysis in social psychology. There are multiple ways in which researchers assess a mediated effect. This manuscript provides an overview of four methods: the Baron & Kenny (1986) method, the product of coefficients approach, percentile bootstrapping, and bias-corrected bootstrapping. These methods are then applied to a social psychology example to assess if people's inferences of a target's tolerance of historically marginalized groups (e.g. "Racial/Ethnic minorities") is a mediator between condition (whether that target is described as a Trump supporter or non-political control) and stigma toward that target. In this example, all methods provided the same results. However, this is not always the case and it is the duty of the researcher to make certain they are using the correct method to assess the mediation effect.

Keywords: Mediation, Baron & Kenny, product of coefficients, percentile bootstrapping, bias-corrected bootstrapping

Introduction

A statistical mediator is a third, intermediate variable that creates a causal chain relationship such that an independent variable causes the mediator, which then causes the dependent variable (MacKinnon, 2008). Mediation is an important tool for understanding the causal chain of relations between three or more variables and is applicable across a wide range of disciplines (e.g., psychology, business, education, treatment, prevention research). Although mediation has application in many fields, the focus of this paper will be mediation as applied in social psychology specifically in a study exploring whether people infer targets who are Trump voters (versus control) to have greater intolerance for historically-marginalized groups, leading to greater stigma toward those Trump-supporting targets.

Mediation has become a prevalent statistical analysis in social psychology. Between the years 2005 and 2009, Rucker and colleagues (2011) examined its use in two leading social psychology journals and found that 59% of research, published in the *Journal of Personality and Social Psychology* (*JPSP*) and 65% from *Personality and Social Psychology Bulletin* (*PSPB*) tested for mediation (Rucker et al., 2011). In July of 2021, I conducted a similar Google Scholar search for the term "mediation" in *JPSP* and *PSPB* articles published between January 2017 and July 2021. The search revealed mediation analysis is still a prominent topic with 48% of articles published by *JPSP* and 51% of articles published by PSPB including the term. Mediation analysis seems to be so prevalent that Bullock et al. (2010) have stated that "mediation analysis is now almost mandatory for new social-psychology manuscripts" (p. 550).

Although mediation is highly prevalent in social psychology research, it is not clear that researchers always best estimate and interpret mediated effects. For example, in 2007 about 77% of the studies that examined mediation never actually tested for the mediated effect, causing some to question if researchers really understand how to analyze mediation (Memon et al., 2017). Similarly, Rucker and colleagues (2011) found that of the studies identified, a bulk of the studies using mediation in *JPSP* and *PSPB* utilized the outdated Baron and Kenny (1986) causal steps approach. However, methodologists have developed additional ways to assess mediation since the influential Baron and Kenny (1986) paper (e.g., Bullock et al., 2010; Memon et al., 2017; Rucker et al., 2011). Confusion about how to best assess mediation effects in research persists. Consequently, methodologists are continually publishing papers regarding best practices in mediation.

Overview of Mediation

Researchers often investigate mediation after first identifying a relationship between an independent and dependent variable. Figure 1 depicts an *X* to *Y* linear regression model (i.e., a direct effect) as characterized by the following regression equation.

$$Y = i_1 + cX + \varepsilon_1 \tag{1}$$

Here, *X* is the independent variable and *Y* is the dependent variable. The arrow indicating the path, *c*, from *X* to *Y* is showing that *X* predicts *Y*; *c* quantifies the relationship between X and *Y*. The value ε_1 is the part of *Y* that is unexplained by its relationship to *X*. In this direct effect equation, the intercept is represented by i_1.

Figure 1.

Direct Effect Between X and Y

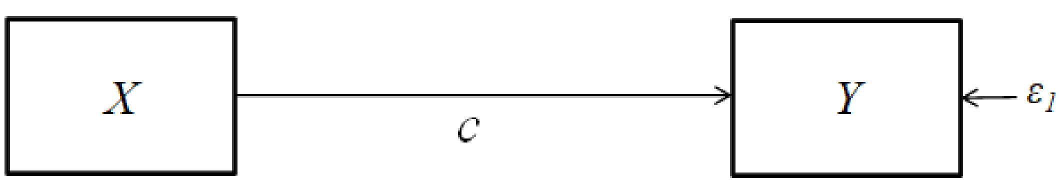


Figure 2 shows a single mediator model. Here, *X* is the independent variable, *Y* is the dependent variable, and *M* is the mediator. Figure 2 is characterized by the following equations.

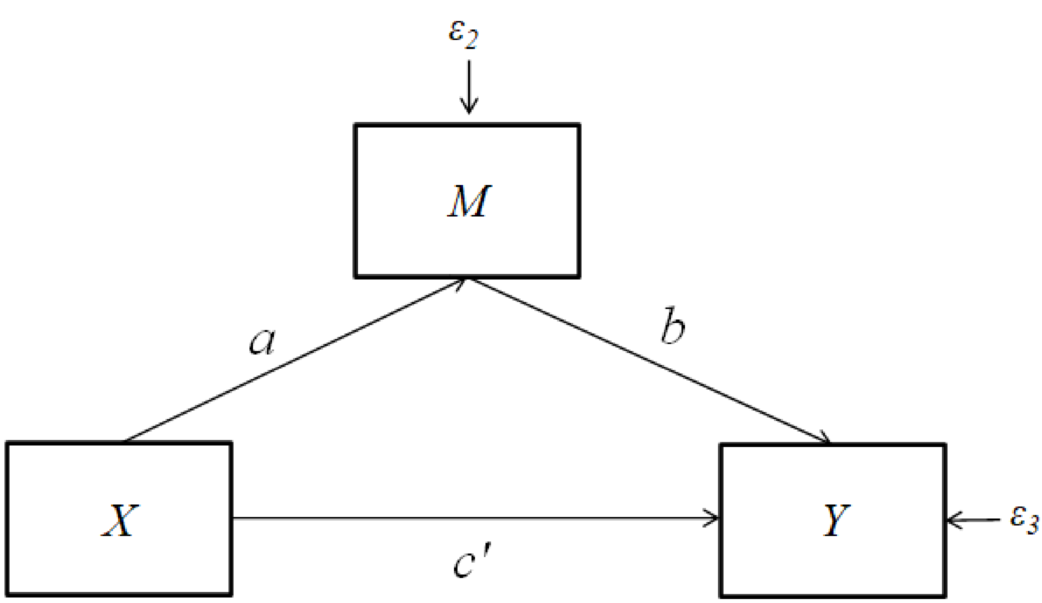
$$M = i_2 + aX + \varepsilon_3 \quad (2)$$

$$Y = i_3 + c'X + bM + \varepsilon_3 \quad (3)$$

Above each path (the arrows) in Figure 2 is a coefficient that represents the relationship between variables; the coefficients correspond with those in Equations 2 and 3. The coefficient *a* represents the relationship between *X* and *M*, *b* represents the relationship between *M* and *Y* controlling for *X*, and *c'* represents the relationship of *X* to *Y* adjusted to account for *M* (the prime in *c'* is used to show that the relationship between *X* and *Y* has been adjusted relative to the *c* path in Figure 1 due to controlling for the mediator). The coefficient ε_2 is the part of *M* that is not explained by *X* and ε_3 corresponds to the part of *Y* that is not explained by *X* and *M* (MacKinnon & Fairchild, 2009). In the equation for this regression model i_2 andi_3 represents the intercepts.

Figure 2.

Single Mediator Model



In a single mediator model, the mediated effect is quantified by either the product of coefficients (*ab*) or by the difference in coefficients (*c-c'*). The product of coefficients calculates mediated effect by multiplying the paths *a* and *b* to show the indirect effect *X* has on *Y* through *M*. The difference in coefficients calculates the mediated effect by taking the relationship between *X* and *Y*, *c*, and subtracting it by the relationship between *X* and *Y* when it is adjusted to account for *M*, *c'* (MacKinnon, 2008). For single mediator linear models with no missing data, these two expressions are equivalent (MacKinnon, 2008). Although, the product of coefficients approach is preferred as it is more broadly generalizable beyond the single mediator model with continuous outcomes (Fairchild & McDaniel, 2017).

There are many variations of techniques to analyze mediation. For the sake of this paper, I will focus on four of the most commonly used methods: Baron and Kenny (1986) method, the product of coefficients approach, percentile bootstrapping, and bias-corrected bootstrapping.

Baron & Kenny (1986) Method

One of the most used, yet highly criticized, tools to test for mediation is the Baron & Kenny (1986) method (Memon et al., 2017). First, the relationship between the *X* and *Y*, denoted by *c* (Equation 1) must prove statistically significant. Then the relationship between *X* and *M*, denoted by *a* (Equation 2), must be statistically significant. Next, *M* and *Y* must have a statistically significant relationship while controlling for *X*, denoted by *b* (Equation 3). Finally, *c'* (Equation 3), the effect of *X* on *Y* when *M* is present must not be statistically significant (Baron & Kenny, 1986). This final step is often relaxed to accommodate "partial" mediation (Rucker et al., 2011). A concern for this analysis is the first requirement that states there should be statistically significant relationship in the *Y* on *X* regression model (Equation 1). Many methodologists claim this specific step is fallible and mediation could still be present even if a statistically significant direct effect is not found (e.g., MacKinnon & Fairchild, 2009). Methodological researchers have also proposed a variant of the Baron and Kenny (1986) approach using a joint significance test of *a* and *b,* testing for statistical significance of *a* and *b* simultaneously, and improving the Baron and Kenny (1986) method slightly (MacKinnon et al., 2002).

Product of Coefficients

The product of coefficients approach uses Equations 2 and 3 to assess mediation. The mediated effect is calculated as the product of the *a* coefficient and the *b* coefficient. This approach utilizes statistical significance testing with a standard *z*- or t-distribution. Researchers calculate a standard error of *ab*, create a test statistic by dividing *ab* by the standard error, and comparing the test statistic to a z- or t-distribution. A variety of standard errors exist, but one commonly used is the Sobel (1982) standard error. The corresponding test statistic with the Sobel (1982) standard error is below.

$$\frac{ab}{\sqrt{a^2 s_b^2 + b^2 s_a^2}} \tag{4}$$

As mentioned, a variety of standard errors exist including corrected variations of the expression in the denominator of the equation above. However, regardless of the formula for standard error, methodological researchers have demonstrated that this method is biased due to the fact that the product of two coefficients is not guaranteed to have symmetrical distribution. Because the product of two coefficients is not necessarily normal or even symmetrical, traditional significance testing and confidence limits comparing test statistics to the symmetrical z- or t-distributions are flawed (MacKinnon et al., 2002). Instead, methodologists suggest that researchers use methods that take into account the distribution of the product of two coefficients is not necessarily normally distributed.

Methods that consider the asymmetric confidence interval to be best practice (e.g., MacKinnon, 2008; MacKinnon, Fairchild, & Fritz, 2007; Fairchild & McDaniel, 2017). There are broadly two methods to do this – 1) have regard to the mathematical properties of the product of the distribution using programs like prodclin (MacKinnon, Fritz, et al., 2007) or rmediation (Tofighi & MacKinnon, 2011) or 2) bootstrapping. This paper focuses on bootstrapping to evaluate methods using asymmetric confidence limits, and I describe bootstrapping below.

Percentile and Bias-Corrected Bootstrapping

Bootstrapping is a resampling technique to test the mediated effect as the product of two coefficients. To begin, researchers take a random sample with replacement out of the original *N* observations, such that this new sample has *N* observations as well, creating a bootstrap sample. This will be repeated at least 1,000 times (MacKinnon, 2008). Next, estimate the indirect effect for all bootstrapped samples. Then a 95% confidence interval is constructed using the 2.5 percentile and the 97.5 percentile from the distribution created from the bootstrapped samples (Shrout & Bolger, 2002). Percentile and bias-corrected bootstrapping are very similar. However, bias-corrected bootstrapping uses the difference of the sample's mediated effect and the average mediated effect in the bootstrapped distribution to correct the bootstrapped percentiles, where percentile bootstrapping does not account for such bias. Bias-corrected bootstrapping is also recommended when the mediated effect of the sample is not equal to zero (MacKinnon, 2008)

Analysis

To illustrate mediation, I evaluated a sample taken from a February 2021 poster presentation, *An intolerance of intolerance? Why people stigmatize Trump voters* (Crosswhite et al., 2021). Data were collected in July 2020 using TurkPrime. For purposes of illustration, I will be assessing whether participants' inferred level of target (in)tolerance of historically marginalized groups (HMGs) mediates the relationship between the target (Trump supporter or age and gender-matched non-Trump supporter) and the reported stigma towards the target.

Participants. Of the original 359 participants responding via TurkPrime, 135 responses were dropped based on bot and attention checks developed by the principal investigator, resulting in a total of 224 US participants (125 female, 1 other; $M_{age} = 38.76,\ SD_{age} = 13.20$). The sample was approximately 73% White, 11% Asian or Asian American, 7% Black or African American, 5% Hispanic or Hispanic American, and 3% Native American, bi- or multi-racial, or other.

Procedure. Participants read a short general description of a target described as either a Trump supporter or age- and gender-matched control target, reported inferences about the target, and then completed stigma measures and demographic questions.

Inferred Tolerance. Inference about the target's (in)tolerance of HMGs were assessed in two ways. First, participants were asked, "How tolerant and supportive of each of the following groups do you think the [target] is?" on a 10-point slider (0 = Not at all tolerant/supportive, 10 = Extremely tolerant/supportive). This question was asked for 15 groups, six being HMGs (i.e., racial/ethnic minorities, women, translate people, gay men, Mexican immigrants, convicted criminals who have served their time). Other groups included traditionally non-marginalized groups and/or groups associated with Trump Support (e.g., gun owners, pro-life, traditional families).

Second, a scale was adapted from previous work on political tolerance (e.g. Vogt, 1997); using this participants responded to how accurate they thought certain statements made about the target were on 7-point Likert-Type scales (1 = Not at all, 7 = very much). There were 32 statements (e.g., “[Target] thinks that [group] should be allowed to make a speech in his city”), split between HMGs and traditionally non-marginalized groups. Scores were then averaged together.

Stigma. Although a variety of scales were used to measure stigma, for the purpose of this study to evaluate the perceived stigma of the target, I used the primary measure which is also common in stigma work: a feeling thermometer (*1* = cold, *10* = *warm*). Lower scores indicate greater coldness and thus stigma toward targets.

Results

I used four methods to evaluate the mediated effect of inferred tolerance on the relationship between Trump supporters and stigma: (1) Baron and Kenny (1986), (2) the product of coefficients, (3) percentile bootstrapping, and (4) bias-corrected bootstrapping. In this scenario, X is the target condition (Trump supporter or control target), M is inferred tolerance of HMGs, and Y is stigma.

Baron and Kenny (1986) Method

To begin, I used the Baron and Kenny (1986) method. In the first step evaluating the direct effect between X and Y (Equation 1), c is significant, ($c = -2.32$, $SE = 0.31$, $t = -7.59$, $p < 0.001$). This means that when the target is a Trump supporter, the predicted value of stigma decreases by 2.32 points relative to the non-Trump supporting target, meaning more stigma is associated with the Trump supporter.

Next, in the assessment of inferred tolerance regressed on target condition (Equation 2), a is significant, showing there is a decrease in inferred tolerance of HMGs when the target is a Trump supporter ($a = -1.79$, $SE = 0.27$, $t = -6.51$, $p < 0.001$).

For the third step, regressing stigma on inferred tolerance controlling for target condition

(Equation 3), *b* is significant, meaning as inferred tolerance of HMGs increases, so does the stigma score towards the target ($b = 0.58$, $SE = 0.06$, $t = 9.03$, $p < 0.001$).

For the final step, *c'* (Equation 3) is significant ($c' = -1.29$, $SE = 0.29$ $t = -4.50$, $p < 0.001$) demonstrating that inferred tolerance of HMGs does not fully mediate the relationship between target condition and stigma.

It should be noted that although the final step is part of Baron and Kenny (1986), as previously mentioned, the requirement of *c*' being non-significant is relaxed to accommodate partial meditation (Rucker et al., 2011). However, methodologists debate whether the notion of partial versus full mediation should even be discussed (e.g. MacKinnon, Fairchild & Fritz, 2007; Memon et al., 2017).

Product of Coefficients

Next, I assessed the data using the product of coefficients tests coupled with the Sobel standard error using M*plus* (v. 8.4; Muthen and Muthen, 1998-2017). Using Equation 4 as described above, the product of coefficients test demonstrated statistically significant mediation ($ab = -1.03$, $SE = 0.20$, $z = - 5.29$, $p < 0.001$). Thus, this method implies that inferred tolerance of HMGs is a significant mediator for the relationship between target condition and stigma.

Although I will see that the same conclusion is reached with the following bootstrapping methods, the methodological literature is clear that the product of coefficients method can be biased because it assumes the product of coefficients has a symmetrical distribution (MacKinnon, Fairchild & Fritz, 2007) and that the bootstrapping approaches discussed next are preferred.

Percentile Bootstrap

Using SPSS PROCESS v. 3.5.3 (Hayes, 2017), I ran a percentile bootstrap with 5,000 bootstrapped samples. Results indicated a statistically significant mediation, using 95% CI (*ab* = -1.03, *SE* = 0.20, *CI* = [-1.44, -0.67]), once again demonstrating that the inferred tolerance of HMGs is a mediator of target condition and stigma. As previously, the direct effect remained statistically significant (*c'* = -1.29, *SE* = 0.29, $p < .001$, *CI* = [-1.85, -0.72]), suggesting that inferred tolerance of HMGs partially mediates the relationship between target condition and stigma.

Bias-Corrected Bootstrap

I again assessed the mediation effect using 5000 bootstrapped samples, but this time using bias-corrected bootstrapping in M*plus* (v. 8.4; Muthen and Muthen, 1998-2017). As mentioned, bias-corrected bootstrapping is a variation of percentile bootstrapping, and I did not anticipate major differences in the results.

As expected, there was a significant mediation effect, (*ab* = -1.03, *SE* = 0.004, CI = [-1.47, -0.69]), again suggesting that the inferred tolerance of HMGs mediates the relationship between target condition and stigma. Likewise, the direct effect remained significant (*c'* = -0.25, *SE* = 020, CI = [-0.35, -0.16]).

Discussion

Each condition came to the same conclusion: the extent to which participants inferred the target to be (in)tolerant of HMGs mediates the relationship between target condition (Trump supporter or not) and the reported stigma towards the target.

Although the different methods did not create differing results for the research question in this particular scenario, the methodological research still clearly demonstrates that methods taking into account the asymmetric confidence intervals such as percentile bootstrapping or bias-corrected bootstrapping are considered best practices when it comes to mediation analysis. I consider some of the issues in existing mediation methods below.

The Baron and Kenny (1986) method has too low of Type I error rate and low power for small and medium effect sizes, as well as too many Type II errors (MacKinnon et al., 2002). While the product of coefficients method does have higher power than the Baron and Kenny (1986) method, the Type I error rates are too low to comfortably test for mediation (MacKinnon et al., 2002). Many methodological researchers recommend using confidence intervals based on bootstrapping, which I used here because it takes into account the non-symmetrical distribution, and also applies to more complicated models (MacKinnon, Fairchild & Fritz, 2007; Shrout & Bolger, 2002).

It should be noted that as mediation applies causal inference, none of these statistical tests are actually testing causal inference – instead, they are testing the mediated effect size and statistical inference. The question of whether or not a researcher got the order of the causal chain correct is largely a research design question.

Ultimately, several methods are used to test for statistical mediation in social psychology. For this example, the different methods provided nearly identical statistical results but the methodological literature is clear that this is not always the case. Hence, as methodologists continue to advance mediation analysis, it is the duty of researchers to continue to adapt their practices to ensure they are presenting research with the proper analysis.

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