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*Expert Tutorial*

# Statistical mediation analysis with a multicategorical independent variable

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Virtually all discussions and applications of statistical mediation analysis have been based on the condition that the independent variable is dichotomous or continuous, even though investigators frequently are interested in testing mediation hypotheses involving a multicategorical independent variable (such as two or more experimental conditions relative to a control group). We provide a tutorial illustrating an approach to estimation of and inference about direct, indirect, and total effects in statistical mediation analysis with a multicategorical independent variable. The approach is mathematically equivalent to analysis of (co)variance and reproduces the observed and adjusted group means while also generating effects having simple interpretations. Supplementary material available online includes extensions to this approach and Mplus, SPSS, and SAS code that implements it.

## 1. Introduction

Statistical mediation analysis is commonplace in psychological science (see, for example, Hayes & Scharkow, 2013). This may be because the concept of mediation gets to the heart of why social scientists become scientists in the first place – because they are curious and want to understand how things work. Establishing that independent variable $X$ influences dependent variable $Y$ while being able to describe and quantify the mechanism responsible for that effect is a lofty scientific accomplishment. Though hard to achieve convincingly (Bullock, Green, & Ha, 2010), documenting the process by which an effect operates is an important scientific goal.

The simple mediation model, the focus of this paper, is diagrammed in Figure 1(b). This model reflects a causal sequence in which $X$ affects $Y$ indirectly through mediator variable $M$. In this model, $X$ is postulated to affect $M$, and this effect then propagates causally to $Y$. This *indirect effect* represents the mechanism by which $X$ transmits its effect on $Y$. According to this model, $X$ can also affect $Y$ directly – the *direct effect* of $X$ – independent of $X$'s influence on $M$. Examples of such a model are found in abundance in psychological science (see Bearden, Feinstein, & Cohen, 2012; Johnson & Fujita, 2012).

The literature on statistical mediation analysis focuses predominantly on models with a dichotomous or continuous independent variable, for this is a requirement of the

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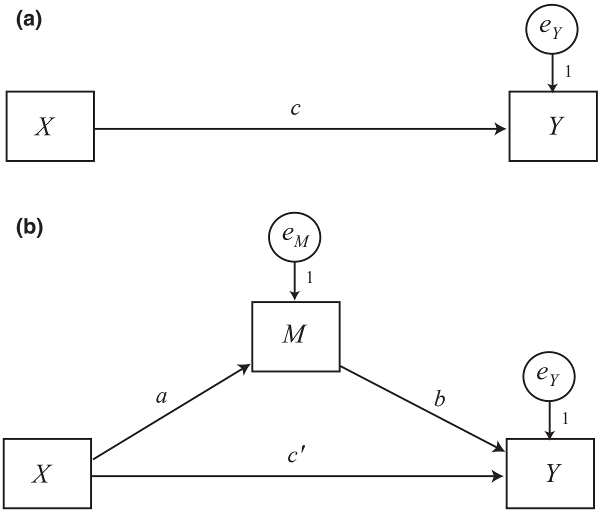



**Figure 1.** A simple mediation model in path diagram form.

path-analytic approach described more formally below that is the foundation of statistical mediation analysis as widely practised. Yet in many studies, the independent variable is *multicategorical*, for example a control group versus two or more experimental conditions. With such a design, and absent any other methodological guidance, researchers resort to outdated methods or otherwise finesse their analytical problem so that it conforms to this requirement of a dichotomous or continuous $X$. For instance, some researchers use a variant of the causal steps method popularized by Baron and Kenny (1986) by assessing whether group differences on $Y$ revealed in an analysis of variance (ANOVA) disappear after controlling for a proposed mediator (see, for example, Pandelaere, Briers, Dewitte, & Warlop, 2010; Wirtz & McColl-Kennedy, 2010). Others have treated a discrete, ordinal independent variable as interval level and used standard regression-based techniques (Chandler & Pronin, 2012; Legault, Gutsell, & Inzlicht, 2011). Alternatively, investigators have modified their data to produce a dichotomous $X$, such as by conducting separate analyses comparing various groups of interest while discarding the remaining data (Pedersen, Denson, Goss, Vasquez, Kelly, & Miller, 2011; Ronay, Greenaway, Anicich, & Galinsky, 2012; Werle, Wansink, & Payne, 2011; Whitchurch, Wilson, & Gilbert, 2011) or collapsing multiple groups into one for comparison with another group or set of groups (Calogero & Jost, 2011; Haisley & Loewenstein, 2011; Ruva, Guenther, & Yarbrough, 2011). Another strategy used is substituting a continuous manipulation check for the multicategorical $X$ and proceeding with a mediation analysis as if $X$ were observed as a continuum (Forgas, 2011).

In response to articles we published on mediation analysis (Preacher & Hayes, 2004, 2008), we have received many inquiries about how to conduct a mediation analysis when $X$ is categorical but not dichotomous. Here we offer the first systematic treatment of this topic in the form of a tutorial describing a method of quantifying indirect and direct effects in statistical mediation analysis involving a categorical variable with at least three levels. Although we are not the first to acknowledge the potential utility of this approach (see MacKinnon, 2008, pp. 372, 374), to date there has been no formal description of how to parameterize the model depending on the hypotheses one wishes to test and how the various effects are interpreted. We introduce the concepts of the *relative indirect*, *direct*, and *total effect* and illustrate how they are estimated and interpreted. Following this, we describe inferential tests of relative effects. Woven throughout are the results of the application of this approach using SPSS, SAS, and Mplus code documented in an online supplement (Appendix S1). Our goal in this paper is to illustrate some ways that groups could be represented in a mediation model and the consequences of the choice on how to interpret the effects that result, while also providing researchers with a means of implementing this approach using popular software.

At the outset, it is important to note that we do not offer a means of assessing cause. Mediation is a causal phenomenon, but no statistical model can prove causality. Causality is established by appropriate research design and logical or theoretical argument. Statistics can be used to ascertain whether an association between variables exists and of what magnitude. This may aid in establishing the soundness of the causal argument, but does not prove it. Yet a statistical model can be used to eliminate certain alternative explanations, and more complex statistical approaches than we discuss here can be used in non-experimental studies when causal inference is less justified due to limitations of the design (such as non-random assignment; see, for example, Hong, 2012; Muthén, 2011; Pearl, 2012). Causal inference can be strengthened if the researcher can argue or demonstrate that the variables are modelled in the appropriate causal sequence, if key effects in a mediation model are not confounded by omitted variables (Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010), and if no important moderation effects go unmodelled (Muller, Yzerbyt, & Judd, 2008; Pearl, 2012; VanderWeele & Vansteelandt, 2009, 2010; Yzerbyt, Muller, & Judd, 2004). For the purposes of this tutorial, we assume that the user of the approach we describe is comfortable with causal claims being made or acknowledges when non-causal interpretations exist and couches those claims appropriately given limitations of the data collection method.

### 1.1. Working example

Our example is based on data provided by Kalyanaraman and Sundar (2006) from an experiment on web portal customization and its effects on users. They proposed that users of a more customized portal would have a more positive attitude toward the portal than those using a less customized portal. They offer various potential mechanisms to explain this effect. We focus here on *perceived interactivity*, a construct receiving much attention in research on human–computer interaction. Kalyanaraman and Sundar reasoned that people feel a customized web portal is more interactive, which translates into a more favourable attitude toward the portal. Thus, they argue that customization influences attitudes at least partly through perceived interactivity.

Sixty participants browsed the web using a MyYahoo! web portal. Prior to arriving at a computer laboratory, participants completed a questionnaire to assess their hobbies, travel interests, favourite sports teams, preferred news sources, and so forth. This information was used to construct a customized web portal for each participant through which they would browse the web during the study. Participants assigned to the high customization condition ($n$ = 20) browsed the web using a portal that was highly customized based on many of their responses to the pretest questionnaire (links to their favourite news pages, reviews of movies they might like, etc.). Participants in the moderate customization condition ($n$ = 20) browsed through a portal that had been moderately customized, using fewer responses to the pretest questionnaire. Participants assigned to the control condition ($n$ = 20) browsed using a portal that had not been customized at all. After a period of web browsing, their attitude toward the portal was

**Table 1.** Descriptive statistics for the web portal customization study

| | Perceived interactivity ($M$) | | Attitude ($Y$) | | |
|---|---|---|---|---|---|
| | $\bar{M}$ | $SD$ | $\bar{Y}$ | $SD$ | $\bar{Y}^*$ |
| Control ($n$ = 20) | 4.250 | 1.839 | 4.335 | 1.647 | 4.792 |
| Moderate ($n$ = 20) | 5.825 | 1.558 | 6.005 | 1.159 | 5.897 |
| High ($n$ = 20) | 6.500 | 1.298 | 7.300 | 0.770 | 6.950 |
| All groups combined | 5.525 | 1.821 | 5.880 | 1.731 | 5.880 |

$\bar{Y}^*$ = adjusted mean, adjusted to the sample mean of perceived interactivity.

assessed (with higher scores reflecting a more positive attitude) as were their perceptions of how interactive they believed the portal to be. Perceived interactivity was assessed using a set of questions designed to measure the extent to which the users perceived the portal as responsive to them and afforded a back-and-forth exchange of information, with higher scores reflecting greater perceived interactivity.

Descriptive statistics can be found in Table 1. A single-factor ANOVA on the attitude measure reveals the expected effect of customization, $F(2, 57) = 28.521$, $p < .001$. Pairwise comparisons between means reveal that those assigned to the highly customized portal ($\bar{Y}_{\text{high}} = 7.300$) had a significantly more positive attitude on average than those assigned to the moderately customized portal ($\bar{Y}_{\text{moderate}} = 6.005$) as well as the control condition ($\bar{Y}_{\text{low}} = 4.335$). Furthermore, those assigned to the moderately customized portal had a more positive attitude to the portal on average than those assigned to the control condition. Thus, it seems attitudes were affected by customization. Whether perceived interactivity is one of the mechanisms driving this effect will be addressed throughout this tutorial.

## 2. Indirect, direct, and total effects

Figure 1 depicts a mediation model with a single mediator $M$ through which $X$ exerts its effect on $Y$. If $M$ and $Y$ are treated as continuous, $X$ is either dichotomous or treated as continuous, and all effects are linear, then the various effects ($c'$, $a$, and $b$ in Figure 1(b)) can be estimated with a set of ordinary least squares (OLS) regressions or simultaneously using a structural equation modelling (SEM) program. Two linear models are required:

$$M = i_1 + aX + e_M, \tag{1}$$

$$Y = i_2 + c'X + bM + e_Y. \tag{2}$$

Of interest are the *indirect effect* of $X$, quantified as the product of $a$ and $b$, and the *direct effect*, quantified as $c'$. The indirect effect, $ab$, is interpreted as the amount by which two cases that differ by one unit on $X$ are estimated to differ on $Y$ as a result of the effect of $X$ on $M$ which in turn affects $Y$. It serves as a quantitative instantiation of the mechanism through which $X$ influences $Y$. The *direct effect* of $X$ quantifies how much two cases equal on $M$ but differing by one unit on $X$ are estimated to differ on $Y$. It quantifies how differences in $X$ relate to differences in $Y$ independent of $M$'s influence on $Y$. The *total effect* of $X$ on $Y$, denoted by $c$ in Figure 1(a), is the sum of $X$'s direct and indirect effects on $Y$, that is $c = c' + ab$. A separate model is not needed to estimate $c$, but it can be estimated from

$$Y = i_3 + cX + e_Y. \tag{3}$$

The total effect is the amount by which two cases that differ by one unit on $X$ are estimated to differ on $Y$ through both the direct and indirect pathways.

This 'one-unit difference on $X$' interpretation does not depend on whether $X$ is dichotomous or continuous. But when $X$ is dichotomous and the two groups are coded with a one-unit difference (e.g., 0 and 1), the indirect and direct effects can be interpreted as mean differences on $Y$. The indirect effect represents the mean difference between the two groups on $Y$ that results from $X$'s influence on $M$ which in turn affects $Y$. The direct effect is the mean difference in $Y$ independent of $X$'s effect on $M$. This direct effect can also be called an *adjusted mean difference* in analysis of covariance (ANCOVA) for it reflects the expected difference between the means of the groups on $Y$ if they were equal on the mediator on average. The total effect is simply the observed difference between the two group means on $Y$.

In more formal mathematical terms, when the two groups are coded with a unit difference on $X$, the observed difference between the group means on $Y$ can be partitioned entirely into the difference due to the indirect effect of $X$ through $M$ and due to the direct effect of $X$. That is,

$$c = (\bar{Y}_{\mathrm{H}} - \bar{Y}_{\mathrm{L}}) = c' + ab = (\bar{Y}^*_{\mathrm{H}} - \bar{Y}^*_{\mathrm{L}}) + (\bar{M}_{\mathrm{H}} - \bar{M}_{\mathrm{L}})b, \tag{4}$$

(see Hayes, 2013), where $\bar{Y}_{\mathrm{H}}$ and $\bar{M}_{\mathrm{H}}$ are the means of $Y$ and $M$ for the group coded one unit higher, $\bar{Y}_{\mathrm{L}}$ and $\bar{M}_{\mathrm{L}}$ are the means of $Y$ and $M$ for the group coded lower, and $\bar{Y}^*_{\mathrm{H}}$ and $\bar{Y}^*_{\mathrm{L}}$ are adjusted means from the parameter estimates from equation (2) but substituting $\bar{M}$ for $M$:

$$\bar{Y}^* = i_2 + c'X + b\bar{M}. \tag{5}$$

### 2.1. When X is a multicategorical variable

When $X$ is multicategorical, these effects cannot be estimated using equations (1) and (2) because there can be no single $a$ or $c'$ that represents $X$'s effect on $M$ or $Y$. The difficulty stems from the fact that in order to fully represent the effect of a categorical variable with $k$ mutually exclusive categories on some dependent variable (whether $M$ or $Y$ in Figure 1), $k - 1$ parameter estimates are needed (see, for example, Cohen, 1968; Cohen, Cohen, West, & Aiken, 2003; Hardy, 1993; Suits, 1957). Absent the ability to model $M$ and $Y$ using equations (1) and (2), researchers interested in examining mediation of the effect of a multicategorical $X$ often resort to aggregating groups or discarding data to produce a dichotomous $X$ and then applying equations (1) and (2). This is neither ideal nor required.

In what follows, we articulate a general linear modelling approach to estimating the direct and indirect effects when $X$ is multicategorical. We rely on the fact that mean differences can be estimated with a linear model by representing groups with a set of $k - 1$ variables, where $k$ is the number of groups. Doing so yields a model mathematically identical to ANOVA and ANCOVA while also exactly reproducing the $k$ group means on $M$

and $Y$ (both unadjusted and adjusted for group differences on $M$). As a consequence, the model, parameter estimates, and model fit statistics (such as $R^2$) retain all the information about how the $k$ groups differ from each other, unlike when groups are collapsed to form a single dichotomous variable. It also allows for simultaneous hypothesis tests if the groups are represented using carefully selected group codes to represent comparisons of interest.

There are many coding strategies that can be used to represent the groups. We first illustrate the analysis using *indicator coding*, also known as *dummy coding*. To dummy-code $k$ groups, $k-1$ dummy variables ($D_i$, $i = 1,\ldots, k-1$) are constructed, with $D_i$ set to 1 if a case is in group $i$, and 0 otherwise. One group is not explicitly coded, meaning all $k-1$ dummy variables are set to 0 for cases in that group. This group functions as the reference category in the analysis, and parameters in the model pertinent to group differences are quantifications relative to this reference group. Using these codes for $X$, the mediation model is parameterized with two equations, one for $M$ and one for $Y$:

$$M = i_1 + a_1 D_1 + a_2 D_2 + \ldots + a_{k-1} D_{k-1} + e_M, \tag{6}$$

$$Y = i_2 + c'_1 D_1 + c'_2 D_2 + \ldots + c'_{k-1} D_{k-1} + bM + e_Y, \tag{7}$$

and represented in path diagram form in Figure 2(b). As in mediation analysis with a continuous or dichotomous $X$, these models can be estimated separately as an OLS regression-based path analysis or simultaneously using SEM.

Estimation of these models yields $k-1$ $a$-coefficients quantifying differences between the groups on $M$, $k-1$ $c'$-coefficients quantifying differences between groups on $Y$ holding $M$ constant, and a single $b$ estimating the effect of $M$ on $Y$ while statistically equating the groups on average on $X$. The direct effect of $X$ on $Y$ is captured in the $k-1$ estimates of $c'_i$ from equation (7), and the indirect effect of $X$ on $Y$ through $M$ is estimated by the $k-1$ products $a_i b$, $i = 1,\ldots, k-1$, from equations (6) and (7).

We adopt the terms *relative indirect effect* and *relative direct effect* to refer to $a_i b$ and $c'_i$, respectively. Of course, effects in virtually any analysis can be thought of as relative to some alternative condition or state of affairs. Our decision to label these effects *relative* formally acknowledges that the direct and indirect effects resulting from the analysis described here will depend on how the independent variable is coded even though the data being analysed are otherwise the same. But regardless of the choice, they will always quantify the effect of being in one group (or set of groups) relative to some reference group or set of groups. For example, in a simple dummy coding system, as in this example, $a_i b$ is the indirect effect on $Y$ via $M$ of being in group $i$ relative to the reference group, and $c'_i$ represents the direct effect of being in group $i$ on $Y$ relative to the reference group. A different choice of reference group will result in different relative effects.

When $X$ is multicategorical, there is no one parameter estimate that can be interpreted as the total effect of $X$. Rather, the total effect is quantified with a set of $k-1$ parameter estimates resulting from the estimation of $Y$ from the $k-1$ dummy variables coding groups in a linear model (see Figure 2(a)):

$$Y = i_3 + c_1 D_1 + c_2 D_2 + \ldots + c_{k-1} D_{k-1} + e_Y. \tag{8}$$

In equation (8) the $k-1$ estimates of $c_i$, $i = 1,\ldots, k$, quantify mean differences between the groups on $Y$. We refer to these $k-1$ estimates as *relative total effects*. In the case of indicator coding, $c_i$ quantifies the mean difference in $Y$ between the group coded with $D_i$

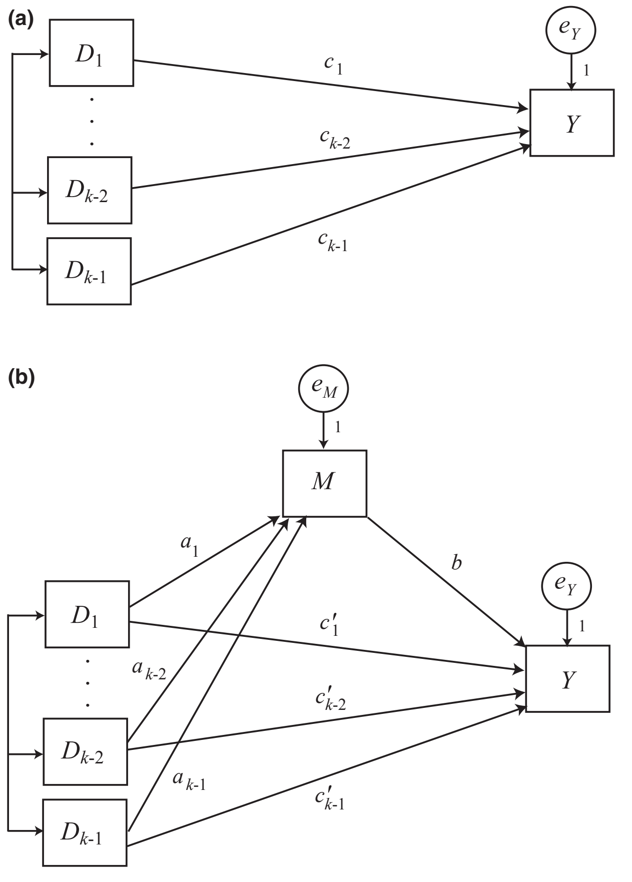



**Figure 2.** A mediation model in path diagram form corresponding to a model with a multicategorical independent variable with *k* categories.

and the reference group. *Regardless of the system used for coding groups*, the relative total effects are equal to the sum of the corresponding relative direct and indirect effects:

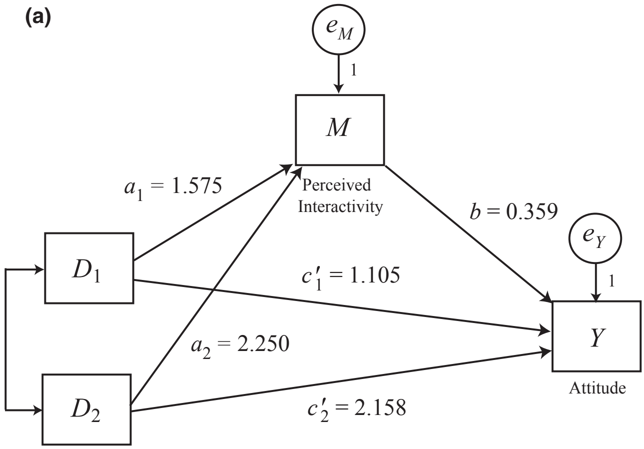
$$c_i = c_i' + a_i b. \tag{9}$$

### 2.2. Example

We illustrate the computation of the relative indirect, direct, and total effects using the web browsing data and the indicator coding system described above and the inset of Figure 3(a). $D_1$ codes the moderate customization condition, $D_2$ codes the high customization condition, and the control group functions as the reference group and receives a code of 0 on $D_1$ and $D_2$.

The coefficients in equations (6), (7), and – optionally – (8) can be estimated using any software capable of estimating a linear model, whether an OLS regression program commonly used by social scientists such as SPSS or SAS, or specialized SEM software such as Mplus, LISREL, or AMOS using maximum likelihood (ML) estimation. Parameter estimates will not be affected by the choice of OLS or ML estimation, but the standard

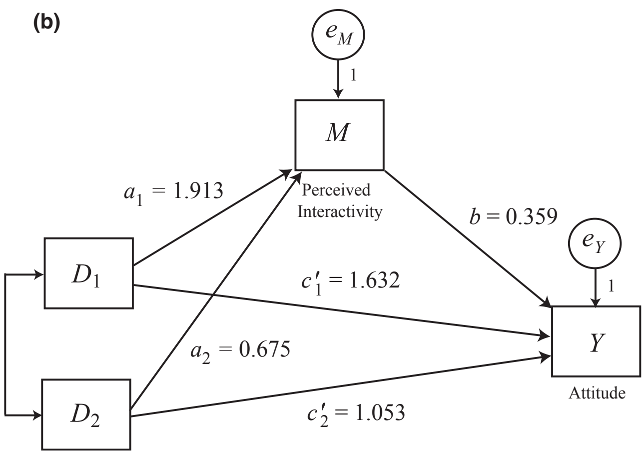
(a)




Indicator coding

| | Control | Moderate | High |
|---|---|---|---|
| $D_1$ | 0 | 1 | 0 |
| $D_2$ | 0 | 0 | 1 |

(b)




Contrast coding

| | Control | Moderate | High |
|---|---|---|---|
| $D_1$ | –0.667 | 0.333 | 0.333 |
| $D_2$ | 0 | –0.500 | 0.500 |

**Figure 3.** Estimated model coefficients resulting from (a) indicator coding and (b) a specific set of contrast codes for customization condition.

errors will differ in smaller samples. This difference dissipates as sample size increases. With the exception of Mplus, most programs do not offer options for generating inferential tests for relative indirect effects discussed later. In the online supplement, we provide Mplus code that yields the regression coefficients in Table 2. Those more comfortable in an OLS regression environment can use the PROCESS or MEDIATE macros for SPSS and SAS (see Hayes, 2013) also described in the online supplement.

Estimating equations (6), (7), and (8) yields $i_1 = 4.250$, $i_2 = 2.810$, $i_3 = 4.335$, $a_1 = 1.575$, $a_2 = 2.250$, $b = 0.359$, $c'_1 = 1.105$, $c'_2 = 2.158$, $c'_1 = 1.670$, and $c'_1 = 2.965$ (see Table 2 or Figure 3(a)). As can be seen by comparing the group statistics in Table 1 to their derivation from the model coefficients in Tables 2 and 3, the models reproduce the group means on $M$ as well as the adjusted and unadjusted group means on $Y$.

The relative indirect effects of $X$ on $Y$ through $M$ are constructed by multiplying $a_1$ and $a_2$ by $b$. In this model, $a_1$ and $a_2$ correspond to the mean differences in perceived interactivity between the moderately and highly customized conditions, respectively, relative to the control condition:

**Table 2.** Estimated coefficients (from equations (6)–(8), estimated in Mplus, PROCESS or MEDIATE) using indicator or contrast coding. Standard errors in parentheses are from Mplus

| Outcome: | | *M* | | *Y* | | |
|---|---|---|---|---|---|---|
| | | Coefficient ($SE$) | | Coefficient ($SE$) | | Coefficient ($SE$) |
| (a) Indicator coding | | | | | | |
| Constant | $i_1$ | 4.250* (0.344) | $i_3$ | 4.335* (0.271) | $i_2$ | 2.810* (0.454) |
| $D_1$ | $a_1$ | 1.575* (0.487) | $c_1$ | 1.670* (0.384) | $c_1'$ | 1.105* (0.370) |
| $D_2$ | $a_2$ | 2.250* (0.487) | $c_2$ | 2.965* (0.384) | $c_2'$ | 2.158* (0.398) |
| $M$ | | | | | $b$ | 0.359* (0.091) |
| (b) Contrast coding | | | | | | |
| Constant | $i_1$ | 5.525* (0.211) | $i_3$ | 5.880* (0.157) | $i_2$ | 3.898* (0.494) |
| $D_1$ | $a_1$ | 1.913* (0.422) | $c_1$ | 2.317* (0.332) | $c_1'$ | 1.632* (0.343) |
| $D_2$ | $a_2$ | 0.675 (0.487) | $c_2$ | 1.295* (0.384) | $c_2'$ | 1.053* (0.347) |
| $M$ | | | | | $b$ | 0.359* (0.091) |

*Statistically significant at no more than the .05 level.

$$a_1 = \bar{M}_{\text{moderate}} - \bar{M}_{\text{control}} = 5.823 - 4.250 = 1.575,$$
$$a_2 = \bar{M}_{\text{high}} - \bar{M}_{\text{control}} = 6.500 - 4.250 = 2.250.$$

Thus, the moderately customized web portal was perceived as 1.575 units more interactive than the non-customized portal, and the highly customized portal was perceived as 2.250 units more interactive than the non-customized portal. Furthermore, holding condition constant, those who perceived the web portal as more interactive also had attitudes that were more positive ($b$ = 0.359). The relative indirect effects of customization are

$$a_1b = 1.575 \times 0.359 = 0.565,$$
$$a_2b = 2.250 \times 0.359 = 0.807.$$

Relative to the control condition, those assigned to the moderately customized condition had attitudes toward the portal that were $a_1b = 0.565$ units more favourable as a result of the positive effect of customization on perceived interactivity (from the sign of $a_1$), which in turn increased the favourability of attitudes (from the sign of $b$). Similarly, those assigned to the highly customized condition had attitudes that were $a_2b$ = 0.807 units more favourable than those assigned to the control condition (from the sign of $a_2$) as a result of the positive effect of high customization on perceived interactivity, which in turn resulted in more favourable attitudes.

**Table 3.** Derivation of group means from the model coefficients

| Condition | | Indicator coding example | Contrast coding example |
|---|---|---|---|
| | $\bar{M}$ | $= i_1 + a_1D_1 + a_2D_2$ | $= i_1 + a_1D_1 + a_2D_2$ |
| Control | 4.250 | = 4.250 + 1.575(0) + 2.225(0) | = 5.525 + 1.913(–0.667) + 0.675(0) |
| Moderate | 5.825 | = 4.250 + 1.575(1) + 2.225(0) | = 5.525 + 1.913(0.333) + 0.675(–0.5) |
| High | 6.500 | = 4.250 + 1.575(0) + 2.225(0) | = 5.525 + 1.913(0.333) + 0.675(0.5) |
| | $\bar{Y}^*$ | $= i_2 + c_1' D_1 + c_2' D_2 + bM$ | $= i_2 + c_1' D_1 + c_2' D_2 + bM$ |
| Control | 4.793 | = 2.810 + 1.105(0) + 2.158(0) + 0.359(5.525) | = 3.898 + 1.631(–0.667) + 1.053(0) + 0.359(5.525) |
| Moderate | 5.897 | = 2.810 + 1.105(1) + 2.158(0) + 0.359(5.525) | = 3.898 + 1.631(0.333) + 1.053(–0.5) + 0.359(5.525) |
| High | 6.950 | = 2.810 + 1.105(0) + 2.158(1) + 0.359(5.525) | = 3.898 + 1.631(0.333) + 1.053(0.5) + 0.359(5.525) |
| | $\bar{Y}$ | $= i_3 + c_1D_1 + c_2D_2$ | $= i_3 + c_1D_1 + c_2D_2$ |
| Control | 4.335 | = 4.335 + 1.670(0) + 2.965(0) | = 5.880 + 2.317(0.667) + 1.295(0) |
| Moderate | 6.005 | = 4.335 + 1.670(1) + 2.965(0) | = 5.880 + 2.317(0.333) + 1.295(–0.5) |
| High | 7.300 | = 4.335 + 1.670(0) + 2.965(1) | = 5.888 + 2.317(0.333) + 1.295(0.5) |

In equation (7), $c'_1$ and $c'_2$ are the relative direct effects of moderate and high customization, respectively, relative to the control condition, and quantify the corresponding differences between adjusted means ($\bar{Y}^*$) on the attitude measure (see Table 1):

$$c'_1 = \bar{Y}^*_{\text{moderate}} - \bar{Y}^*_{\text{control}} = 5.897 - 4.792 = 1.105,$$
$$c'_2 = \bar{Y}^*_{\text{high}} - \bar{Y}^*_{\text{control}} = 6.950 - 4.792 = 2.158.$$

Adjusting for group differences in perceived interactivity, those who browsed using a moderately customized web portal reported attitudes that were 1.105 units more favourable than those who browsed using a non-customized portal, and those who browsed with a highly customized portal had attitudes 2.157 units more favourable than those who browsed using a non-customized portal.

The relative total effects, $c_1$ and $c_2$, can be found in Table 2. These are equivalent to the mean difference in attitudes between the moderate and high customization conditions relative to the control condition, respectively:

$$c_1 = \bar{Y}_{\text{moderate}} - \bar{Y}_{\text{control}} = 6.005 - 4.335 = 1.670,$$
$$c_2 = \bar{Y}_{\text{high}} - \bar{Y}_{\text{control}} = 7.300 - 4.335 = 2.965.$$

These relative total effects can also be calculated by adding the corresponding relative direct and indirect effects $c_1 = c'_1 + a_1 b = 1.105 + 0.565 = 1.670$, and $c_2 = c'_2 + a_2 b = 2.158 + 0.807 = 2.965$.

The relative total, direct, and indirect effects calculated above are all scaled as mean differences in a metric of $Y$ that, in this example, is arbitrary. Dividing each of these effects by the standard deviation of $Y$ (or standardizing $Y$ prior to analysis) results in effects that can be interpreted as a standardized mean difference analogous to Cohen's $d$, and equation (9) still holds. Even so, a standardized version of an arbitrary scale is still arbitrary; standardized effect size measures are not necessarily any more meaningful theoretically or practically than unstandardized measures, and unstandardized effects can be meaningful if the scaling is inherently meaningful or widely used in a research area (see Preacher & Kelley, 2011). Expressing a relative direct or indirect effect as a ratio relative to its corresponding relative total effect, while tempting, has documented problems as an effect size measure and so we discourage doing so. The quantification and interpretation of effect size are an evolving and controversial topic in statistical mediation analysis and elsewhere. Moreover, whether an effect can be deemed large or small is not entirely a statistical question. See Hayes (2013), Kelley and Preacher (2012), and Preacher and Kelley (2011) for a discussion of various measures and controversies.

## 3. Statistical inference

Statistical inference for the total and direct effects of $X$ is straightforward and uncontroversial. For relative direct and total effects, all regression routines programmed into statistical packages that are widely used, as well as most SEM programs, provide standard errors for these effects for testing the null hypothesis of no relative effect using level of significance $\alpha$. Alternatively, $100(1 - \alpha)\%$ confidence intervals (CI) can be constructed as the point estimate plus or minus $t_{\alpha/2}$ standard errors, where $t_{\alpha/2}$ is the value of $t$ that cuts off the upper and lower $100(\alpha/2)\%$ of the $t(df)$ distribution from the rest of the distribution, with degrees of freedom (*df*) equal to the residual degrees of freedom in the models of $Y$ (i.e., equations (7) and (8)).[1]

Using the indicator coding strategy, as can be seen in Table 2, all relative direct and total effects in the web browsing analysis are positive and statistically different from zero for all comparisons ($D_1$, moderate customization versus control; $D_2$, high customization versus control). Regardless of whether or not perceived interactivity is controlled, customization seems to engender more favourable attitudes to the portal.

### 3.1. Inference for relative indirect effects

Until recently, the causal steps approach dominated the practice of statistical mediation analysis. This approach focuses on estimating each of the pathways in the model in Figure 1 and then conducting significance tests for each of the effects while qualitatively comparing the size of the direct effect and total effect of $X$. If certain criteria are met, then it can be said that $M$ mediates the effect of $X$ on $Y$. A formal statistical test of the indirect effect is not required by this approach. Rather, its existence is inferred logically through the rejection of various null hypotheses about the individual paths and the size of the direct relative to the total effect of $X$.

This causal steps approach can be and has been used when $X$ is a multicategorical variable. But for reasons already documented in the mediation analysis literature (see Hayes, 2009, 2013; Rucker, Preacher, Tormala, & Petty, 2011), we advise researchers to eschew methods that rely on testing components of the indirect effect (i.e., $a_i$ and $b$) in favour of a formal inferential test of the product of $a_i$ and $b$. Evidence that at least one relative indirect effect is different from zero supports the conclusion that $M$ mediates the effect of $X$ on $Y$.

Of the many methods one could use for statistical inference about relative indirect effects (see MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; MacKinnon, Lockwood, & Williams, 2004), we advocate the asymmetric bootstrap CI. We prefer this method because it does not make the unwarranted assumption of normality of the sampling distribution of the relative indirect effect, it performs well as evidenced in numerous simulation studies (Biesanz, Falk, & Savalei, 2010; Hayes & Scharkow, 2013; MacKinnon *et al.*, 2004; Williams & MacKinnon, 2008), and it is easy to implement in existing software such as Mplus, SPSS, and SAS using the code provided in the online supplement.

A *percentile* bootstrap CI for a relative indirect effect is constructed by repeatedly taking samples of size $n$ with replacement from cases in the data (e.g., participants in the study), where $n$ is the size of the original sample, and estimating all the coefficients in the mediation model using equations (6) and (7) in each bootstrap sample. From the estimated coefficients, the relative indirect effects are calculated. Repeated $j$ times (ideally $j$ = 5,000 or more), the distributions of $j$ relative indirect effects serve as empirical approximations of their sampling distributions. A $100(1 - \alpha)\%$ CI for each relative indirect effect is constructed as the bootstrap estimates that define the lower and upper $100(\alpha/2)\%$ of the distribution of $j$ estimates, respectively. The relative indirect effect is deemed statistically different from zero if the CI does not straddle zero.

[1] An omnibus test of the total and direct effects of $X$ could be conducted using the $F$-ratio with $k - 1$ and $df_{\text{error}}$ degrees of freedom from an ANOVA or ANCOVA respectively, or from corresponding regression statistics.

Adjustments to the CI endpoints have been offered to produce the *bias-corrected* or *bias-corrected and accelerated* bootstrap CI (see Efron & Tibshirani, 1993). There is some evidence that the percentile bootstrap method is preferable in some circumstances, as the bias-corrected methods have a slightly inflated Type I error rate when one of the two paths in the mediation process is zero (see Fritz, Taylor, & MacKinnon, 2012; Hayes & Scharkow, 2013). Otherwise, the bias-corrected bootstrap CI is more powerful.[2]

Using indicator coding with the control group as the reference group and with the aid of SPSS, SAS, or Mplus code in the online supplement yields 95% bias-corrected bootstrap CIs for the relative indirect effects that do not straddle zero (based on 10,000 bootstrap samples), indicating that both customization conditions (relative to the control condition) indirectly influence attitudes through perceived interactivity (moderate customization, 95% CI = 0.169 to 1.255; high customization, 95% CI = 0.334 to 1.659). This supports a claim that perceived interactivity functions as a mediator of the effect of customization on attitudes. Historically, this result would be described as 'partial mediation' because the corresponding relative total and direct effects of customization are both statistically different from zero. But this term (along with 'complete mediation') has recently been heavily criticized. For reasons discussed in Hayes (2013) and Rucker *et al*. (2011), we recommend not couching the interpretation of the indirect effect in such terms that rely on the outcome of tests of significance of the relative direct or total effects.[3]

### 3.2. Multiple test correction

When $X$ is a multicategorical variable, the number of possible tests one could conduct in a mediation analysis as described above can be large, and we encourage researchers to be mindful of the problems this can produce. A researcher concerned about Type I error inflation resulting from reliance on several inferential tests of relative effects could choose to adjust $p$-values or base inferences on CIs greater than 95%. For instance, with a three-level $X$ and assuming independent adjustments for the sets of two relative direct, indirect, and total effects, a Bonferroni approach to multiple test correction would involve the use of a $p$-value criterion of .025 for rejection of a null hypothesis or a 97.5% CI that does not straddle zero before claiming that a relative effect is different from zero. Doing so in the example above does not change the results or their substantive interpretation. A more (or less) conservative adjustment could be employed depending on the number of tests being conducted in the analysis overall, disciplinary norms, or one's beliefs about the relative risks and costs of Type I relative to Type II errors.

[2] In principle, bootstrap CIs could be used for inference about relative and total direct effects. But there is little statistical advantage to doing so because, unlike the relative indirect effect, the sampling distributions of these effects are typically normal or nearly so.

[3] There is a limitation of this approach to mediation analysis that is important to acknowledge. Because estimates of relative indirect effects will depend on the coding used to represent groups, it is conceivable that one could find evidence of mediation of $X$'s effect on $Y$ by $M$ for one coding choice but not for another, depending on the sizes of the indirect effects relative to the reference group. We have proposed an inferential test of the *omnibus indirect effect* that we believe overcomes this limitation, but it is still being evaluated. See the documentation for MEDIATE at www.afhayes.com for a definition and discussion.

## 4. Alternative coding systems

Indicator coding is not the only system for representing groups. Which coding system to use will be guided by specific questions the investigator wants to answer, and the choice will influence how the relative indirect, direct, and total effects are interpreted. Below we illustrate the computation and interpretation of these effects using one alternative: unweighted contrast coding.

To illustrate this approach, we constructed $k-1$ variables (two in this case) coding two contrasts, one corresponding to the control condition relative to the two customization conditions combined, and the second comparing to the two customization conditions. Using well-disseminated rules for the construction of contrasts (see, for example, Keppel & Wickens, 2004; Rosenthal & Rosnow, 1985), the codes corresponding to the first contrast are –2, 1, and 1 for the control, moderate, and high conditions, respectively. For the second contrast the codes are 0, –1, and 1. Even if only one contrast is of substantive interest, it is still important that the additional $k-2$ sets of contrast codes be specified and included in the models of $Y$ and $M$. Failure to do so will yield a model that does not reproduce the group means.

Although not mathematically necessary, we recommend a transformation of the contrast codes so that the largest and smallest codes in a set differ by only one unit. This scales all relative direct, indirect, and total effects on a mean difference metric (see, for example, West, Aiken, & Krull, 1996). This is accomplished by dividing each of the codes in the $k-1$ sets by the absolute value of the difference between the largest and smallest contrast codes in the set. For example, the first set contains three codes (–2, 1, 1) the largest and smallest which differ by 3 units, and the second set contains codes with a maximum absolute difference of 2. Thus, the resulting transformed codes become –2/3, 1/3, and 1/3 for the first set and 0, –1/2, and 1/2 for the second set. Therefore, $D_1$ and $D_2$ are defined for each condition as $D_1 = -0.667$, $D_2 = 0$ for control, $D_1 = 0.333$, $D_2 = -0.5$ for moderate customization, $D_1 = 0.333$, $D_2 = 0.5$ for high customization (see Figure 3(b)).

With $D_1$ and $D_2$ constructed in this manner, estimation of the coefficients in equations (6)–(8) yields $i_1 = 5.525$, $i_2 = 3.898$, $i_3 = 5.880$, $a_1 = 1.913$, $p < .001$; $a_2 = 0.675$, $p = .166$; $b = 0.359$, $p < .001$, $c'_1 = 1.631$; $p < .001$; and $c'_2 = 1.053$, $p = .002$; $c_1 = 2.317$, $p < .001$; $c_2 = 1.295$, $p < .002$ (see Table 2). Comparing the statistics in Table 1 to their derivation from the model coefficients in Tables 2 and 3 verifies that the resulting models reproduce the group means on $M$ as well as the adjusted and unadjusted group means on $Y$.

The relative indirect effects are estimated as products of coefficients just as when indicator coding is used, and the SPSS and SAS macros or Mplus code described in the online supplement can be used to generate bootstrap CIs for inference. The relative indirect effect for the first contrast comparing any customization to the control condition is the contrast for perceived interactivity,

$$\begin{aligned} a_1 &= \frac{\bar{M}_{\text{moderate}} + \bar{M}_{\text{high}}}{2} - \bar{M}_{\text{control}} \\ &= \frac{5.825 + 6.500}{2} - 4.250 = 1.913, \end{aligned}$$

multiplied by the effect of interactivity on attitudes independent of customization condition, $b = 0.359$:

$$a_1 b = 1.913 \times 0.359 = 0.687.$$

Any customization results in a more favourable attitude by 0.687 units as a result of greater perceptions of interactivity in the customized portals (from the sign of $a_1$), which in turn leads to a more favourable attitude (from the sign of $b$). A 95% bias-corrected bootstrap CI for this relative indirect effect is from 0.259 to 1.387. This relative indirect effect is positive and statistically different from zero.

The relative indirect effect for the second contrast corresponds to the effect of high versus moderate customization on attitudes through perceived interactivity. The contrast for perceived interactivity corresponds to the difference in mean perceived interactivity between the high and moderate customization conditions,

$$a_2 = \bar{M}_{\text{high}} - \bar{M}_{\text{moderate}} = 6.500 - 5.825 = 0.675.$$

When multiplied by the effect of perceived interactivity on attitudes ($b$), the result is the relative indirect effect of high versus moderate customization on attitudes,

$$a_2 b = 0.675 \times 0.359 = 0.242.$$

High customization yields attitudes that are 0.242 units more favourable on average relative to moderate customization due to the greater perceptions of interactivity that result from more customization (from the sign of $a_2$), which in turn positively influences attitudes (from the sign of $b$). But a 95% bias-corrected bootstrap CI for this relative indirect effect straddles zero (from –0.033 to 0.720). Thus, the evidence is not sufficiently strong to claim an indirect effect of high relative to moderate customization.[4]

The relative direct effect $c'_1$ corresponds to the effect of *any* customization on attitudes relative to none, independent of perceived interactivity. The relative direct effect $c'_2$ is the effect of high relative to moderate customization on attitudes independent of perceived interactivity. These relative direct effects correspond to differences between adjusted means, in the former case an unweighted combination of the means in the two customization conditions:

$$\begin{aligned} c'_1 &= \frac{\bar{Y}^*_{\text{moderate}} + \bar{Y}^*_{\text{high}}}{2} - \bar{Y}^*_{\text{control}} \\ &= \frac{5.897 + 6.950}{2} - 4.792 = 1.632, \\ c'_2 &= \bar{Y}^*_{\text{high}} - \bar{Y}^*_{\text{moderate}} = 6.950 - 5.897 = 1.053. \end{aligned}$$

Independent of the effect of perceptions of interactivity on attitude, any customization yields attitudes that are 1.632 units more favourable on average relative to no customization. Furthermore, high customization yields attitudes that are 1.053 units more favourable on average than moderate customization. Tests of significance available in standard regression output or using the code described in the online supplement can be used for inference about these relative direct effects.

[4] A Bonferroni correction of 2 applied to each set of tests does not change the results in this example.

The relative total effects, $c_1$ and $c_2$, are estimated using equation (8) or by adding the corresponding relative direct and indirect effects. These relative total effects of customization on attitudes quantify the mean difference in attitudes toward the portal for any customization relative to none ($c_1$) and high relative to moderate customization ($c_2$):

$$\begin{aligned} c_1 &= \frac{\bar{Y}_{\text{moderate}} + \bar{Y}_{\text{high}}}{2} - \bar{Y}_{\text{control}} \\ &= \frac{6.005 + 7.300}{2} - 4.335 = 2.317, \\ c_2 &= \bar{Y}_{\text{high}} - \bar{Y}_{\text{moderate}} = 7.300 - 6.005 = 1.295. \end{aligned}$$

Observe that these relative total effects partition into the relative direct and indirect effects $c_1 = c_1' + a_1 b = 1.632 + 0.675 = 2.317$ and $c_2 = c_2' + a_2 b = 1.053 + 0.242 = 1.295$. Standard regression output contains inferential tests for these relative total effects.

Any coding system used in ANOVA could be applied to mediation analysis in this fashion. For example, if the independent variable is discrete and ordinal, Helmert coding could be used to estimate the relative effects of category *j* relative to the aggregate of all ordinally higher levels. In the online supplement, we provide an illustration using sequential coding, also useful for discrete, ordinal independent variables. For a discussion of various coding strategies, see Cohen *et al.* (2003), Davis (2010), Hardy (1993), Kaufman and Sweet (1974), Serlin and Levin (1985), Wendorf (2004), and West *et al.* (1996).

## 5. Between-group heterogeneity in the effect of *M* on *Y*

An assumption frequently described as necessary for causal inference in mediation analysis is the *no-interaction assumption* or, in ANCOVA terms, *homogeneity of regression*: the effect of *M* on *Y* is invariant across values of *X*. If this assumption is violated, it is not sensible to estimate a relative indirect effect as $a_i b$ because *b* in equation (7) does not accurately characterize the association between *M* and *Y*, which is contingent on *X* and thus not a single number. Furthermore, interaction between *X* and *M* implies that at least one relative direct effect depends on *M*.

This assumption can be tested by including interaction terms in the model of *Y*. This is accomplished by respecifying the model of *Y* in equation (7) as

$$\begin{aligned} Y = i_2 + c_1' D_1 + c_2' D_2 + \ldots + c_{k-1}' D_{k-1} + b_1 D_1 M + b_2 D_2 M + \ldots \\ + b_{k-1} D_{k-1} M + b_k M + e_Y, \end{aligned} \tag{10}$$

and testing the null hypothesis that all population $b_i$, $i = 1,\ldots, k-1$, equal zero. Rejection implies that the effect of *M* on *Y* depends on *X*. When using OLS regression, this test is implemented using hierarchical variable entry in which $R^2$ from the model in equation (7) is subtracted from $R^2$ from equation (10) to yield $\Delta R^2$. Under the null hypothesis of no interaction, $df(\Delta R^2)/[(1 - R^2)(k - 1)]$ follows the $F(k-1, df)$ distribution, where *df* and $R^2$ are the residual degrees of freedom and squared multiple correlation, respectively, from the model in equation (10). Alternatively, using SEM, the fit of two models can be compared, one with all $b_i$, $i = 1,\ldots, k-1$, constrained to be zero versus one with them freely estimated. Under the null hypothesis of no interaction, the difference in $\chi^2$ for the two models follows the $\chi^2(k-1)$ distribution. If the *p*-value for this test is below $\alpha$, then the assumption of homogeneity of regression has been violated. The outcome of either test will be invariant to the choice of coding system.

In this example, the difference in $R^2$ between the two models of attitudes toward the web portal (*Y*) with and without the $k-1$ products representing the interaction between web customization condition and perceived interactivity was $\Delta R^2 = .004$ and not statistically significant, $F(2,54) = .297$, $p = .744$. Thus, the homogeneity of regression assumption is not contradicted by the data. If the test instead suggested a violation of this assumption, the relative direct and indirect effects calculated as described above will mischaracterize the effect of *X* to a degree dependent on the size of the interaction.

This assumption of no interaction between *X* and *M* represents a special case of the assumption that one's model is properly specified. Because both *X* and *M* are available in the data, this is easy to test and we recommend doing so. Yet in principle any of the paths in a mediation model could be moderated by other variables, and a failure to include such interactions potentially also represents a misspecification that is as important as the assumption that *X* does not interact with *M*. It is routine for researchers to either ignore such possibilities or empirically test for them. Principles described in the literature on 'moderated mediation' (Edwards & Lambert, 2007; Muller, Judd, & Yzerbyt, 2005; Preacher, Rucker, & Hayes, 2007) could be extended to models with a multicategorical independent variable, including the case where *X* and *M* interact. How to do so is beyond the scope of this tutorial.

## 6. Summary

In this tutorial, we have illustrated a method for estimating indirect, direct, and total effects in statistical mediation analysis with a multicategorical independent variable. These relative effects quantify the effects of being in one category on some outcome relative to some other group or set of groups used as a reference for comparison. The outcome of tests of relative effects will be dependent on the choices one makes about coding groups and which group or groups are used as the reference for comparison purposes. Possible extensions to this method are abundant, and in an online supplement we discuss confounding, random measurement error, multiple mediators, and an additional example using sequential coding of groups. We hope this tutorial will facilitate the implementation of this approach and enable researchers to apply the advice given recently by methodologists who study mediation analysis to research designs that include a multicategorical independent variable.

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## Supporting Information

The following supporting information may be found in the online edition of the article:

**Appendix S1.** Statistical mediation analysis with a multicategorical independent variable

Online supplement to Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology*, 67, 451-470. DOI: 10.1111/bmsp.12028

This document contains instructions for the implementation of the method described in Hayes and Preacher (2014) using Mplus as well as using the PROCESS and MEDIATE macros for SPSS and SAS. Following the code, various miscellaneous issues and extensions are addressed, including interpretation of model coefficients using sequential group coding, accounting for random measurement error, dealing with confounds statistically, and models with multiple mediators.

### *Mplus Code Corresponding to the Web Portal Customization Example*

Any structural equation modeling program can produce estimates of the coefficients in a mediation model. Mplus offers features such as bootstrap confidence intervals for indirect effects and inferential tests for functions of parameters that make it a particularly good choice for the kind of analysis we describe in the manuscript. Importantly, the constraints of the freely available demonstration version of Mplus (available from http://www.statmodel.com/) do not preclude its use for estimation of mediation models with a single mediator and a categorical independent variable with as many as three levels. The code below implements the method described in the manuscript and can easily be adapted to mediation analysis with multiple mediators, latent variables, or an independent variable with more than three levels.



```
DATA:
  FILE is c:\sri.txt;
VARIABLE:
  NAMES are cond custom attitude inter;
  USEVARIABLES are attitude inter d1 d2;

!indicator coding
DEFINE:
  if (cond eq 1) then d1 = 0;
  if (cond eq 1) then d2 = 0;
  if (cond eq 2) then d1 = 1;
  if (cond eq 2) then d2 = 0;
  if (cond eq 3) then d1 = 0;
  if (cond eq 3) then d2 = 1;

!model definition
MODEL:
     inter ON d1 (a1)
              d2 (a2);
attitude ON inter (b)
              d1 (cp1)
              d2 (cp2);

!relative indirect effects;
MODEL INDIRECT:
  attitude IND inter d1;
  attitude IND inter d2;
MODEL CONSTRAINT:
  new (tot1 tot2);
  tot1=a1*b;
  tot2=a2*b;
```

The resulting output is below. This output was used to construct parts of Table 2 in the manuscript.

```
MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 INTER    ON
    D1                 1.575      0.487      3.233      0.001
    D2                 2.250      0.487      4.619      0.000

 ATTITUDE ON
    INTER              0.359      0.091      3.965      0.000
    D1                 1.105      0.370      2.985      0.003
    D2                 2.158      0.398      5.426      0.000

 Intercepts
    ATTITUDE           2.810      0.454      6.187      0.000
    INTER              4.250      0.344     12.338      0.000

 Residual Variances
    ATTITUDE           1.166      0.213      5.477      0.000
    INTER              2.373      0.433      5.477      0.000

 New/Additional Parameters
    TOT1               1.670      0.384      4.353      0.000
    TOT2               2.965      0.384      7.728      0.000


TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from D1 to ATTITUDE

  Sum of indirect      0.565      0.226      2.506      0.012

  Specific indirect

    ATTITUDE
    INTER
    D1                 0.565      0.226      2.506      0.012


Effects from D2 to ATTITUDE

  Sum of indirect      0.807      0.268      3.008      0.003

  Specific indirect

    ATTITUDE
    INTER
    D2                 0.807      0.268      3.008      0.003
```

For contrast coding as described in the text, replace the DEFINE section above with

```
!orthogonal contrast coding
DEFINE:
  if (cond eq 1) then d1 = -0.667;
  if (cond eq 1) then d2 = 0;
  if (cond eq 2) then d1 = 0.333;
  if (cond eq 2) then d2 = -0.5;
  if (cond eq 3) then d1 = 0.333;
  if (cond eq 3) then d2 = 0.5;
```

For sequential coding as discussed later in this supplement, replace the DEFINE section of the core program with

```
!sequential coding
DEFINE:
  if (cond eq 1) then d1 = 0;
  if (cond eq 1) then d2 = 0;
  if (cond eq 2) then d1 = 1;
  if (cond eq 2) then d2 = 0;
  if (cond eq 3) then d1 = 1;
  if (cond eq 3) then d2 = 1;
```

To generate 95% and 99% bias corrected bootstrap confidence intervals for relative indirect effects (as well as all other parameter estimates), add the lines below to the program. For percentile confidence intervals, change "bcbootstrap" below to "bootstrap".

```
ANALYSIS:
bootstrap = 10000;

OUTPUT:
cinterval (bcbootstrap);
```



***Estimation using PROCESS for SPSS and SAS***

PROCESS is a freely-available regression-based path analysis macro for both SPSS and SAS that estimates the model coefficients in mediation and moderation models of various forms while also providing modern inferential methods for inference about indirect effects including bootstrap confidence intervals. Its use in mediation analysis is described in Hayes (2013) along with documentation of its many features, and can be downloaded from [web address withheld for peer review])

One documented limitation of PROCESS is that only a single $X$ variable can be specified in a mediation model, and it must be either dichotomous or continuous. However, with the strategic use of covariates, manual construction of the indicator codes prior to execution, and multiple executions of the macro, PROCESS can estimate a model as in Figure 2 of the manuscript. The results generated by PROCESS will be identical to what Mplus generates, with the exception of standard errors which will tend to be slightly smaller than OLS standard errors in smaller samples. These differences in standard errors dissipate rapidly as sample size increases.

The example SPSS PROCESS code and output below corresponds to the analysis of the web portal customization study using indicator coding of customization condition. Variables named ATTITUDE and INTER contain measurements of attitudes toward the web portal and perceived interactivity, respectively, and variable COND codes experimental condition (1 = control, 2 = moderate customization, 3 = high customization).

Because PROCESS allows only a single independent variable that must be either dichotomous or continuous, it must be tricked into estimating a model with a multicategorical independent variable. This is done by running PROCESS $k - 1$ times, where $k$ is the number of levels of the independent variable, and using $k - 1$ group codes constructed prior the execution of PROCESS. At each run, one of the group codes is used as $X$ and the others as covariate(s), with the code serving as $X$ being swapped with a covariate at subsequent PROCESS runs. So that the same bootstrap samples are used in consecutive executions, the random number generator should be seeded using the **seed =** command, with the same seed used time. This seed can be chosen arbitrarily.

This code first constructs two dummy variables coding experimental condition with the control condition (cond = 1) as the reference category. The following PROCESS command then executes a mediation model with the first dummy variable as $X$ and the other as a covariate. This generates estimates of $a_1$, $a_2$, $b$, $c_1$, $c_2$, $c'_1$, and $c'_2$ corresponding to the values in Table 2 of the manuscript, as well as a bias-corrected bootstrap confidence interval for $a_1b$ based on 10,000 bootstrap samples. The summary table at the end includes the three effects of $X$, which in this case are the relative total, direct, and indirect effects for moderate customization relative to the control condition ($c_1$, and $c'_1$, and $a_1b$), in that order.



```
  compute d1=(cond=2).
  compute d2=(cond=3).
  process vars=attitude inter d1 d2/y=attitude/m=inter/x=d1/total=1/
      model=4/boot=10000/seed=3423.
```

```
Model = 4
    Y = attitude
    X = d1
    M = inter

Statistical Controls:
CONTROL= d2

Sample size
         60

***************************************************************************
Outcome: inter

Model Summary
          R       R-sq          F        df1        df2          p
      .5220      .2725    10.6734     2.0000    57.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.2500      .3534    12.0256      .0000     3.5423     4.9577
d1           1.5750      .4998     3.1512      .0026      .5742     2.5758
d2           2.2500      .4998     4.5018      .0000     1.2492     3.2508
```

```
**************************************************************************

Outcome: attitude

Model Summary
          R       R-sq          F        df1        df2          p
      .7771      .6039    28.4646     3.0000    56.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.8100      .4701     5.9772      .0000     1.8682     3.7517
inter         .3588      .0937     3.8302      .0003      .1712      .5465
d1           1.1048      .3831     2.8842      .0056      .3375     1.8722
d2           2.1576      .4116     5.2423      .0000     1.3331     2.9821

************************** TOTAL EFFECT MODEL ****************************
Outcome: attitude

Model Summary
          R       R-sq          F        df1        df2          p
      .7072      .5002    28.5213     2.0000    57.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.3350      .2783    15.5749      .0000     3.7776     4.8924
d1           1.6700      .3936     4.2426      .0001      .8818     2.4582
d2           2.9650      .3936     7.5326      .0000     2.1768     3.7532

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     1.6700      .3936     4.2426      .0001      .8818     2.4582

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     1.1048      .3831     2.8842      .0056      .3375     1.8722

Indirect effect of X on Y
          Effect    Boot SE   BootLLCI   BootULCI
inter      .5652      .2724      .1643     1.2665

******************* ANALYSIS NOTES AND WARNINGS **************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
    10000

Level of confidence for all confidence intervals in output:
    95.00
```



Missing from the output above is the relative indirect effect for high customization relative to none ($a_2b$) along with a bootstrap confidence interval for inference. The code below generates this relative indirect effect by switching `d1` and `d2` in the **`x=`** specification. Most of the output is identical to the code generated by the command above, so that output is suppressed by using the **`detail=0`** option. Using the same random number seed as in the prior run of

PROCESS produces a bootstrap confidence interval based on the same set of bootstrap samples. The effects for $X$ in this summary table are the relative total, direct, and indirect effects for high customization relative to the control condition ($c_2$, $c'_2$, and $a_2b$), in that order.

```
  process vars=attitude inter d1 d2/y=attitude/m=inter/x=d2/total=1/
     model=4/boot=10000/seed=3423/detail=0.
```

```
Model = 4
    Y = attitude
    X = d2
    M = inter

Statistical Controls:
CONTROL= d1

Sample size
         60

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     2.9650      .3936     7.5326      .0000     2.1768     3.7532

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     2.1576      .4116     5.2423      .0000     1.3331     2.9821

Indirect effect of X on Y
          Effect    Boot SE   BootLLCI   BootULCI
inter      .8074      .3273      .3217     1.6442

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
    10000

Level of confidence for all confidence intervals in output:
    95.00
```



The SPSS compute commands above generate indicator codes with the control group as the reference group. The commands to generate the contrast codes used in the example analysis would be

```
  if (cond=1) d1 = -0.667.
  if (cond=1) d2 = 0.
  if (cond=2) d1 = 0.333.
  if (cond=2) d2 = -0.5.
  if (cond=3) d1 = 0.333.
  if (cond=3) d2 = 0.5.
```

For the sequential coding example described below, the following SPSS commands construct the sequential codes:

```
compute d1 = (cond > 1).
compute d2 = (cond > 2).
```

The PROCESS macro is available for SAS but requires PROC IML. The command structure is very similar to the SPSS version, but the construction of group codes requires commands that are different than those used in SPSS. The SAS code below conducts the example analysis using indicator coding of groups, assuming the data reside in a SAS data file named “web”:

```
data web;set web;d1=(cond=2);d2=(cond=3);run;
%process (data=web,vars=attitude inter d1 d2,y=attitude,m=inter,x=d1,
   total=1,model=4,boot=10000,seed=3423);
%process (data=web,vars=attitude inter d1 d2,y=attitude,m=inter,x=d2,
   total=1,model=4,boot=10000,seed=3423,detail=0);
```

For the contrast codes corresponding to the example analysis in this paper, change the DATA line to read:

```
data web;set web;
if (cond=1) then do;d1=-0.667;d2=0;end;
if (cond=2) then do;d1=0.333;d2=-0.5;end;
if (cond=3) then do;d1=0.333;d2=0.5;end;
run;
```

For the sequential codes described in the example below, the DATA line should read

```
data web;set web;d1=(cond>1);d2=(cond>2);run;
```



***Estimation using MEDIATE for SPSS***

MEDIATE is a freely available SPSS macro (downloadable from [web address blinded for review]) that facilitates the estimation of mediation models with multicategorical independent variables along with the ability to generate bootstrap confidence intervals for indirect effects. It is very limited in its features relative to PROCESS, but it does have one handy option that automates the construction of codes for a categorical independent variable. The code and output below corresponds to the analysis of the web portal customization study using indicator coding of customization condition. Variables named ATTITUDE and INTER contain measurements of attitudes toward the web portal and perceived interactivity, respectively, and variable COND codes experimental condition (1 = control, 2 = moderate customization, 3 = high customization). The **`catx=1`** option specifies indicator coding and sets the control condition as the reference group. See the documentation for additional information about the MEDIATE macro and its options.

**mediate y=attitude/x=cond/m=inter/samples=10000/total=1/catx=1.**

```
Run MATRIX procedure:

VARIABLES IN THE FULL MODEL:
    Y = attitude
   M1 = inter
    X = cond

CODING OF CATEGORICAL X FOR ANALYSIS:
    cond       D1       D2
  1.0000    .0000    .0000
  2.0000   1.0000    .0000
  3.0000    .0000   1.0000

*****************************************************************************

OUTCOME VARIABLE:
   attitude

MODEL SUMMARY (TOTAL  EFFECTS MODEL)
          R       R-sq   Adj R-sq          F        df1        df2          p
      .7072      .5002      .4826    28.5213     2.0000    57.0000      .0000

MODEL COEFFICIENTS (TOTAL EFFECTS MODEL)
             Coeff.       s.e.          t          p
Constant     4.3350      .2783    15.5749      .0000
D1           1.6700      .3936     4.2426      .0001
D2           2.9650      .3936     7.5326      .0000

*****************************************************************************

OUTCOME VARIABLE:
   inter

MODEL SUMMARY
          R       R-sq   Adj R-sq          F        df1        df2          p
      .5220      .2725      .2469    10.6734     2.0000    57.0000      .0001



MODEL COEFFICIENTS
             Coeff.       s.e.          t          p
Constant     4.2500      .3534    12.0256      .0000
D1           1.5750      .4998     3.1512      .0026
D2           2.2500      .4998     4.5018      .0000

*****************************************************************************

OUTCOME VARIABLE:
   attitude

MODEL SUMMARY
          R       R-sq   adj R-sq          F        df1        df2          p
      .7771      .6039      .5827    28.4646     3.0000    56.0000      .0000
```

```
MODEL COEFFICIENTS
             Coeff.       s.e.          t          p
Constant     2.8100      .4701     5.9772      .0000
inter         .3588      .0937     3.8302      .0003
D1           1.1048      .3831     2.8842      .0056
D2           2.1576      .4116     5.2423      .0000

TEST OF HOMOGENEITY OF REGRESSION (X*M INTERACTION)
            R-sq          F        df1        df2          p
inter      .0043      .2969     2.0000    54.0000      .7443

*****************************************************************************

INDIRECT EFFECT(S) THROUGH:
 inter

       Effect   SE(boot)       LLCI       ULCI
D1      .5652      .2694      .1693     1.2548
D2      .8074      .3252      .3338     1.6587


----------

********************* ANALYSIS NOTES AND WARNINGS *************************

NOTE: Indicator coding is used for categorical X
Number of samples used for indirect effect confidence intervals:   10000
Level of confidence for confidence intervals:  95.0000

Bias corrected bootstrap confidence intervals for indirect effects are
printed in output
```



***Sequential Coding of Groups***

In the web portal customization study, the three levels of the manipulation can be rank ordered with respect to degree of customization (none, moderate, or high). When the categories of a multicategorical predictor can be so ordered, sequential coding can be useful. With sequential codes, the relative direct and indirect effects can be interpreted as the effects of membership in one group relative to the group one step sequentially lower in the ordered system. Darlington (1990, pp. 236-237) describes sequential coding for a categorical variable with any number of ordered categories. With only three groups, the coding is relatively simple. For the control condition (the lowest level of customization), $D_1$ and $D_2$ are set to 0, for the moderately customized condition (the next highest level of customization), $D_1 = 1$, $D_2 = 0$, and for the highest level of customization, $D_1 = D_2 = 1$.

Estimating the coefficients in Equations 6, 7, and 8 in the manuscript yields the following results: $i_1 = 4.250$, $i_2 = 2.810$, $i_3 = 4.335$, $a_1 = 1.575$, $p = 0.001$; $a_2 = 0.675$, $p = 0.166$; $b = 0.359$, $p < 0.001$; $c'_1 = 1.105$, $p = 0.003$; $c'_2 = 1.053$, $p = .002$; $c_1 = 1.670$, $p < .001$; $c_2 = 1.295$, $p <$ 0.002. As with the other two methods of coding groups described in the manuscript, the resulting models reproduce the group means on $M$ as well as $Y$ (adjusted and unadjusted).

The relative indirect effects are still estimated as products of coefficients. The $a_1$ coefficients quantify the mean differences in perceived interactivity between the moderate customization and control condition ($a_1$) and between the high and moderate customization conditions ($a_2$). That is,

$$a_1 = \overline{M}_{moderate} - \overline{M}_{control} = 5.825 - 4.250 = 1.575$$

and

$$a_2 = \overline{M}_{high} - \overline{M}_{moderate} = 6.500 - 5.825 = 0.675.$$

When $a_1$ and $a_2$ are multiplied by the effect of interactivity on attitudes, holding customization condition constant ($b = 0.359$), the result is the relative indirect effects of customization on attitudes through perceived interactivity:

$$a_1 b = 1.575(0.359) = 0.565$$

and

$$a_2 b = 0.675(0.359) = 0.242.$$

The relative indirect effect $a_1 b$ estimates the indirect effect of moderate customization relative to none through perceived interactivity on attitudes. Those who browsed using a moderately customized portal had attitudes that were 0.565 units more favorable on average (with a 95% bias-corrected bootstrap confidence interval from 0.169 to 1.255) than those assigned to the noncustomized portal condition as a result of this indirect mechanism linking customization to attitudes through perceived interactivity. The relative indirect effect $a_2 b$ estimates the indirect effect of high relative to moderate customization through perceived interactivity. Browsing with a highly customized portal resulted in attitudes that were 0.242 units more favorable on average than browsing using a moderately customized portal as a result of this indirect mechanism linking customization to attitudes through perceived interactivity. Zero cannot be rejected as a plausible value for this indirect effect, as a 95% bias-corrected bootstrap confidence interval straddled zero (-0.043 to 0.710).

Using this coding system, the relative direct effect $c'_1$ corresponds to the effect of moderate customization on attitudes relative to none, independent of perceived interactivity, and the relative direct effect $c'_2$ is the effect of high customization relative to moderate customization. This corresponds to differences between the adjusted means:

$$c'_1 = \overline{Y}^*_{moderate} - \overline{Y}^*_{control} = 5.897 - 4.792 = 1.105$$
$$c'_2 = \overline{Y}^*_{high} - \overline{Y}^*_{moderate} = 6.950 - 5.897 = 1.053.$$

As when other coding systems are used, the relative total effects can be estimated using Equation 8 in the manuscript or by adding the relative direct and indirect effects. With sequential coding, $c_1$ estimates the mean difference in attitude between the moderately customized and control groups, and $c_2$ estimates the mean difference in attitude between the highly customized and moderately customized groups. That is,

$$c_1 = \overline{Y}_{moderate} - \overline{Y}_{control} = 6.005 - 4.335 = 1.670$$
$$c_2 = \overline{Y}_{high} - \overline{Y}_{moderate} = 7.300 - 6.005 = 1.295.$$

As both effects are positive, this suggests attitudes increase in favorability as customization increases. Finally, notice that as with indicator or contrast coding, the relative total effects partition cleanly into the relative direct and relative indirect effects: $c_1 = c'_1 + a_1b = 1.105 + 0.565 = 1.670$ and $c_2 = c'_2 + a_2b = 1.053 + 0.242 = 1.295$.

### *Random Measurement Error*

The example analyses in the manuscript and this supplement ignore the potential influence of random measurement error in $X$, $M$, or $Y$. In experiments, and even when $X$ is an observed categorical variable, measurement error in $X$ is often negligible to nonexistent unless the categories were constructed through some kind of artificial categorization of a continuum or there is some ambiguity or subjectivity in the decision as to which category a particular case in the data belongs. But $M$ and/or $Y$ may and often do contain some random measurement error, such as when they are sum scores from a psychological test, personality inventory, or attitude scale. If $M$, $Y$, or both is measured with error, the result is bias in the estimation of the effects of $X$, reduced statistical power, or both (see, e.g., Darlington, 1990, pp. 201-204; Ledgerwood & Shrout, 2012).

The method described in the manuscript can easily be extended using Mplus or another SEM program using single indicator latent variables with reliability-weighted errors (see e.g., Kline, 2005) or latent variable model with a measurement model component that links the latent variable causally to its indicators. Both approaches potentially reduce at least some of the deleterious effects of random measurement error. As with any measurement model, the researcher should ascertain whether the measurement model for the latent variable(s) satisfies various criteria for claiming "good fit," for direct and indirect effects linking latent variables that are not modeled well have little substantive meaning. For discussions of latent variable mediation analysis, see Cheung and Lau (2008), Coffman and MacCallum (2005), Lau and Cheung (2012), and MacKinnon (2008).



### *Multiple Mediators*

The approach we have illustrated for estimating relative indirect and direct effects can be extended to models with any number ($m$) of mediators operating in parallel. Figure S1 depicts a model with $m$ proposed mediators and a multicategorical $X$ with $k$ categories. The relative total effects, $c_i$, can be estimated if desired using Equation 8 in the manuscript, whereas the relative indirect and direct effects are pieced together from parameter estimates from $m + 1$ linear models, one for each of the $m$ mediators and one for $Y$:

$$M_j = i_{1j} + a_{1j}D_1 + a_{2j}D_2 + \ldots + a_{(k\text{-}1)j}D_{k\text{-}1} + e_{Mj} \tag{S1}$$
$$Y = i_2 + c'_1D_1 + c'_2D_2 + \ldots + c'_{k\text{-}1}D_{k\text{-}1} + b_1M_1 + b_2M_2 + \ldots + b_mM_m + e_Y \tag{S2}$$

The same relationships among relative total, indirect, and direct effects exist in multiple-mediator models as in single-mediator models. The relative total effect for $D_i$ can be partitioned into the relative direct effect for $D_i$ plus the sum of the *relative specific indirect effects* for $D_i$, $a_{i1}b_1 + a_{i2}b_2 + \ldots + a_{im}b_m$. That is,

$$c_i = c_i' + \sum_{j=1}^{m} a_{ij} b_j \tag{S3}$$

This last term in Equation S3 is the *relative total indirect effect* of $D_i$. Each relative specific indirect effect quantifies the component of the relative total indirect effect that is carried uniquely through that mediator. Inferential tests of relative specific indirect effects can be undertaken just as described in the manuscript, and these would typically be the focus of a mediation analysis. The Mplus code above can be modified without difficulty to include multiple mediators, and the PROCESS and MEDIATE procedures for SPSS and SAS allow for multiple mediators operating in parallel in this fashion. See the documentation.

### *Covariates and Confounds*

In a mediation model, the interpretation of an indirect effect as a causal one assumes that the mediator $M$ is causally located between $X$ and $Y$. That is, it is assumed that $X$ causes $M$ and $M$ causes $Y$. When $X$ is experimentally manipulated and sound experimental procedures are followed, a causal association between $X$ and $M$ and between $X$ and $Y$ is established by showing that the $k$ groups differ on $M$ and $Y$ on average. Of course, as many others have emphasized before us (e.g., Bullock et al., 2010; Hayes, 2013; Mathieu, DeShon, & Bergh, 2008; Stone-Romero & Rosopa, 2010), this does not establish that $M$ causes $Y$. It could be that $Y$ causes $M$ or that $M$ and $Y$ are spuriously associated (both are caused by some variable $W$) or epiphenomenally associated ($M$ is correlated with the "true" intermediary variable $W$). If $X$ is not experimentally manipulated, such threats to causal inference also exist in the interpretation of the association between $X$ and $M$ as well.

Spuriousness and epiphenomenality, as alternative explanations at least with respect to a given competing variable $W$, can be accounted for in a mediation model by including $W$ as an additional predictor or "covariate" in the models of $M$ and $Y$. For example, Equations 1, 2, and 3 in the manuscript with the inclusion of $W$ as a covariate would be

$$M = i_1 + aX + d_1W + e_M \tag{S4}$$
$$Y = i_2 + c'X + bM + d_2W + e_Y \tag{S5}$$
$$Y = i_3 + cX + d_3W + e_Y \tag{S6}$$

The addition of covariates is simple in any OLS regression program; covariates can be added to each of the ON statements in the Mplus code above, and the PROCESS and MEDIATE macros also accept covariates.



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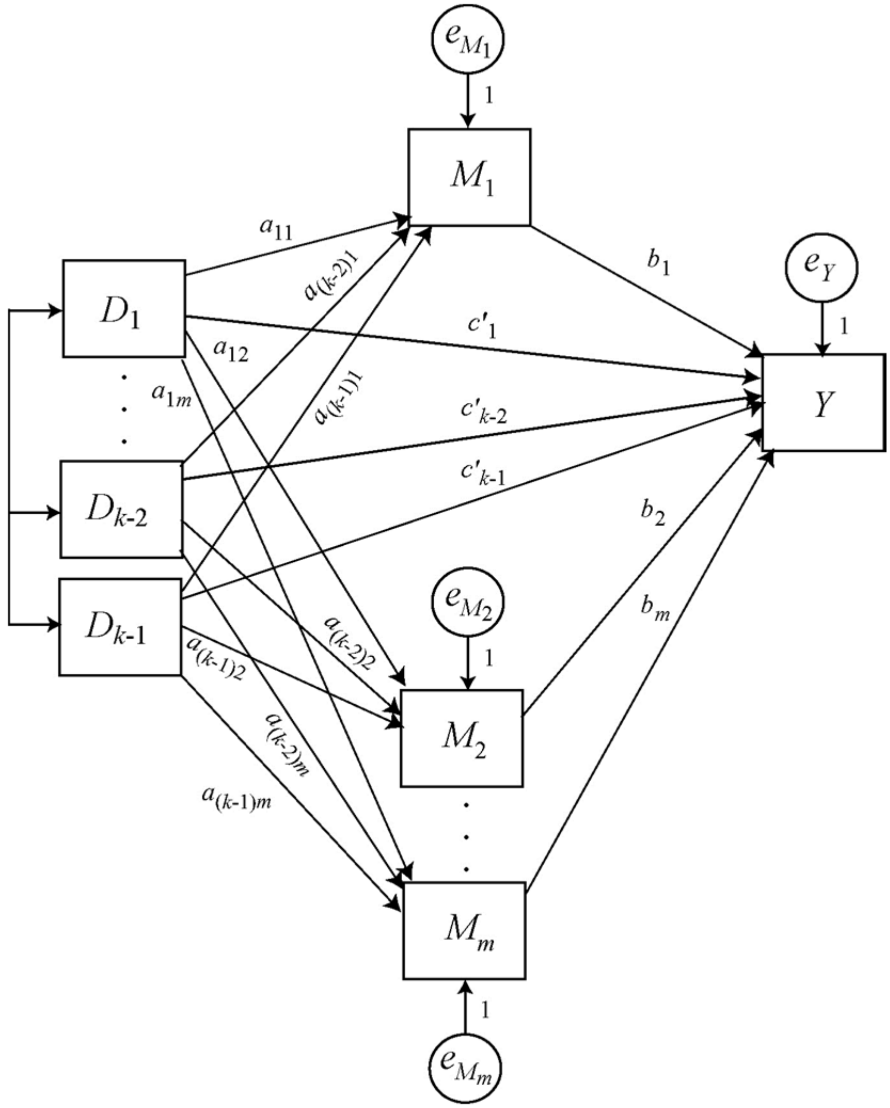


Figure S1. A multiple mediation model in path diagram form corresponding to a model with an independent variable *X* with *k* categories and *m* mediators operating in parallel. When estimating using a structural equation modeling program, it is recommended that the covariance between mediator errors be freely estimated (see e.g., Preacher and Hayes, 2008).