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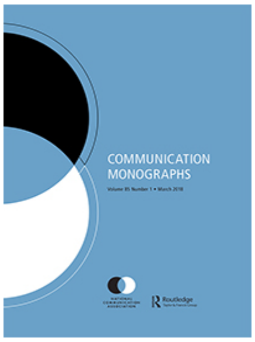

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Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation

Andrew F. Hayes

Department of Psychology, The Ohio State University, Columbus, OH, USA

ABSTRACT
Mediation of *X*'s effect on *Y* through a mediator *M* is moderated if the indirect effect of *X* depends on a fourth variable. Hayes [(2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, 50, 1–22. doi:10.1080/00273171.2014.962683] introduced an approach to testing a moderated mediation hypothesis based on an *index of moderated mediation*. Here, I extend this approach to models with more than one moderator. I describe how to test if *X*'s indirect effect on *Y* is moderated by one variable when a second moderator is held constant (partial moderated mediation), conditioned on (*conditional moderated mediation*), or dependent on a second moderator (*moderated moderated mediation*). Examples are provided, as is a discussion of the visualization of indirect effects and an illustration of implementation in the PROCESS macro for SPSS and SAS.

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Understanding the processes by which effects operate, and the boundary conditions of those effects, is one of the primary goals of science. In the realm of communication science, better understanding exists when we can claim *how* some communication-related event or phenomenon (e.g., how a news story is framed, the kind of social support a person receives during a time of crisis) affects an outcome or response (e.g., an emotional reaction to a news event or a personal crisis, how mobilized a person becomes to take an action) and for whom or in what context that effect exists or does not, or is strong versus weak, or positive versus negative. Although there are many ways a researcher can establish the mechanism by which an effect operates and its boundary conditions, all of which are reliant on solid research design and substantive theory above all else, statistical mediation and moderation analysis are popular statistical methods used to explore questions about how (mediation, or *indirect effects*) and under what circumstance (moderation, or *conditional effects*) effects operate. Many journal articles and even a few books have been written on this topic to help researchers understand and implement various approaches to moderation and mediation analysis (Hayes, 2018; MacKinnon, 2008; VanderWeele, 2015).

If it is true that deeper understanding of an effect exists when one grasps the mechanism by which an effect operates and when that effect exists and when it does not, being able to describe the boundary conditions of mechanisms reflects even greater understanding.

CONTACT Andrew F. Hayes hayes.338@osu.edu

Conditional process analysis, a term coined by Hayes (2018; Hayes & Preacher, 2013), is an analytical strategy focused on quantifying the boundary conditions of mechanisms and testing hypotheses about the contingent nature of processes, meaning whether "mediation is moderated." Although the history of analysis focused on the "when of the how" goes back to at least the 1980s (James & Brett, 1984; Judd & Kenny, 1981), in the last 10 years or so, methodologists have provided researchers with various analytical approaches, all very similar though differing in emphasis, to answering the question as to whether mediation is moderated (e.g., Edwards & Lambert, 2007; Fairchild & MacKinnon, 2009; Hayes, 2015; Hayes & Preacher, 2013; Muller, Judd, & Yzerbyt, 2005; Preacher, Rucker, & Hayes, 2007; Wang & Preacher, 2015). Analytically, these approaches attempt to address whether an indirect effect (mediation) is dependent on another variable (moderation).

There are many examples of communication researchers using these methods to estimate and test conditional process models. Lee and Jang (2013) found that among people less interested in social affiliation, exposure to a celebrity's Twitter feed (compared to just reading a news story containing the Twitter content) resulted in a greater sense of social presence which, in turn, enhanced parasocial interaction and willingness to watch one of the celebrity's movies. But among people higher in affiliation tendencies, presence was reduced by exposure to the Twitter feed, which, in turn, lowered these same outcomes. Affiliative tendency moderated the indirect effect of exposure to the Twitter feed through social presence. Igartua and Frutos (2017) found that relative to a film that focused on positive intergroup contact with immigrants, a film that aroused empathy toward immigrants resulted in stronger identification with immigrants, which, in turn, resulted in a more positive attitude toward immigration, but this mechanism (i.e., the indirect effect) was larger among those with less prejudice. Among more prejudiced viewers, there was no indirect effect of the empathy-inducing film on immigration attitudes through identification. Prejudice moderated the indirect effect of the empathy narrative. Some additional examples of the use of conditional process analysis in the communication literature include Beullens and Vandenbosch (2016), Feldman (2013), Hart (2013), and Goodboy, Martin, and Brown (2016).

To date, analytical treatments of conditional process analysis in the literature have focused on simple models with a single moderator.[1] Yet not all conditional process models that researchers want to test are so simple. Sometimes investigators studying communication processes test models in which an effect in a causal system (i.e., a pathway of influence, either from causal agent to mediator, or from mediator to outcome) is moderated by more than one variable, additively (i.e., two 2-way interactions; e.g., Dixon, 2016; Trucco, Colder, & Wieczorek, 2011), multiplicatively (a three-way interaction; e.g., Krieger & Sarge, 2013), or both paths are moderated, each by a different moderator variable (e.g., Armstrong, Carmody, & Janicke, 2014; Laran, Dalton, & Andrade, 2011; Li, Shaffer, & Bagger, 2015). The literature is largely silent on how to tackle these more complex models.

This manuscript advances the literature by introducing new concepts and mathematical approaches to estimating and making inferences about the conditional nature of mechanisms in conditional process models with more than one moderator. After reviewing the fundamentals, it builds on the approach described by Hayes (2015) based on the *index of moderated mediation* already being used by researchers. I introduce the concepts of *partial moderated mediation*, *conditional moderated mediation*, and *moderated moderated* *mediation*, along with corresponding indices used to test whether and to what extent an indirect effect is moderated in a model with two moderators. The indices of partial and conditional moderated mediation quantify the linear relationship between a moderator and an indirect effect when a second moderator is held constant (partial moderated mediation) or at a given value of the second moderator (conditional moderated mediation). A third index – of moderated moderated mediation – quantifies how quickly the relationship between a moderator and an indirect effect is changing as a second moderator changes. I also discuss visualizing and probing of moderation of mediation in these more complex models.

Before beginning, it is important to emphasize that mediation models are causal models, and valid causal inference requires far more than just establishing an association between variables through some kind of statistical analysis. The assumptions of causal inference in mediation analysis (see Preacher, 2015, for a discussion) are hard to meet even in experiments and are sometimes difficult or even impossible to test. I use causal language here loosely, recognizing that there are non-causal interpretations for associations observed in the examples I provide. I take the position that statistics has fairly little to say about whether two variables are *causally* related, but it has much to contribute to researchers by providing descriptive and inferential tools that can be used to quantify effects that might be causal and to test hypotheses about potentially causal relationships. Ultimately, inferences are products of our minds rather than our mathematics, and there is no substitute for good theory, research design, and strong logical argument when interpreting research results and statistical outcomes.

Fundamentals: Indirect effects, moderation, and moderated mediation

The simplest mediation model specifies a single mediator M causally located between X and Y, as in Figure 1, panel A. Assuming linear effects, X is dichotomous or an interval-level continuum, and M and Y are treated as quantitative and measured at the interval level or higher (assumptions made in the rest of this manuscript for all models discussed), the parameters of this model are typically estimated in practice with two ordinary least squares regression equations

$$\hat{M} = i_M + aX \tag{1}$$

$$\hat{Y} = i_Y + c'X + bM, \tag{2}$$

with errors in estimation of M and Y (not denoted in Equations (1) or (2) or the remaining equations in this manuscript) assumed to be normal, independent, and identically distributed with means of zero. Assuming no interaction between X and M, the indirect effect of X on Y is the product of a and b, and the direct effect of X on Y is c'. A mediation hypothesis is tested statistically by estimating and conducting an inference about the indirect effect, as it quantifies the difference in Y attributable to a one unit change in X through the effect of X on M which in turn affects Y.[2]

In a moderation model, the effect of X on Y is specified as related to a moderator W, as in Figure 1, panel B. Researchers testing a moderation hypothesis using linear regression most often assume that the relationship between X and Y is linear and also linearly

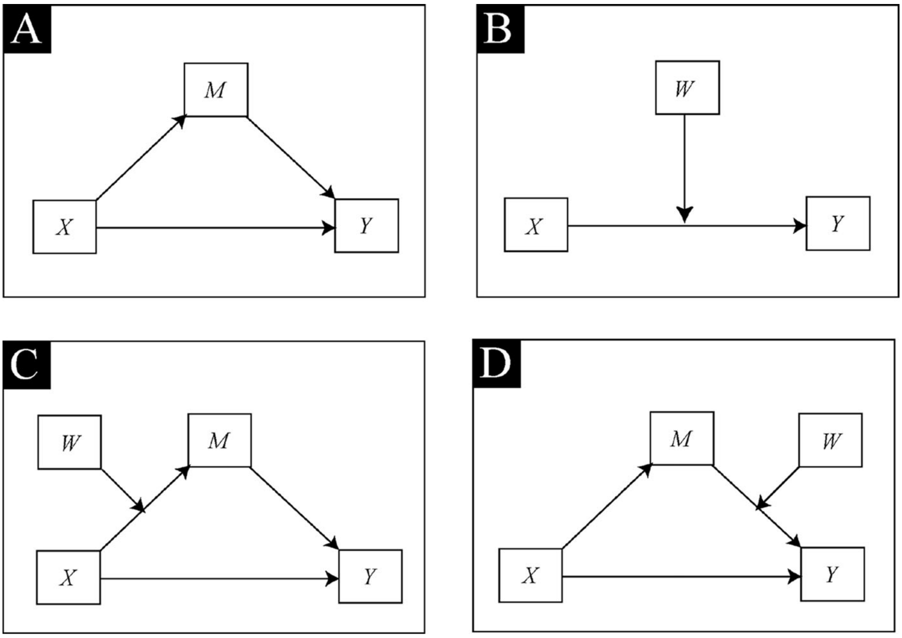

Figure 1. Simple mediation (A), moderation (B), and first (C) and second stage (D) moderated mediation models.

moderated by W, and therefore estimate a model of Y of the form

$$\hat{Y} = i_Y + b_1X + b_2W + b_3XW, \tag{3}$$

where W is either dichotomous or a quantitative variable measured at the interval level or higher. In this model, X's effect on Y is $\theta_{X\rightarrow Y} = b_1 + b_3W$ and thus a linear function of W. This can be seen by expressing Equation (3) in an alternative form:

$$\hat{Y} = i_Y + \theta_{X\rightarrow Y}X + b_2W = i_Y + (b_1 + b_3W)X + b_2W.$$

A linear moderation hypothesis is tested with an inference about the regression weight for XW in Equation (3). If this weight is different from zero, this implies that X's effect on Y varies with W. With affirmative evidence of moderation, researchers then probe it using such methods a "simple slopes analysis" or the Johnson–Neyman technique (Bauer & Curran, 2005; Darlington & Hayes, 2017; Hayes & Matthes, 2009).

Moderation and mediation analysis can be analytically integrated. For example, the effect of X on M in a mediation model can be estimated as linearly moderated by W (see Figure 1, panel C). Using regression analysis, this *first stage moderated mediation* model is estimated with

$$\hat{M} = i_M + a_1X + a_2W + a_3XW$$

$$\hat{Y} = i_Y + c'X + bM.$$

From these two equations, the indirect effect of X on Y is the product of the effect of X on M $(a_1 + a_3W)$ and the effect of M on Y (b)

$$(a_1 + a_3W)b = a_1b + a_3bW \tag{4}$$

(Edwards & Lambert, 2007; Hayes, 2015; Preacher et al., 2007), which is a linear function of W. As the indirect effect is the statistical quantification of the mechanism through which X affects Y, when it is a linear function of a moderator, it means the mechanism's size or strength increases or decreases with changes in the moderator. The inclusion of W and XW in the model of Y would allow the direct effect of X to be moderated by W, though that would not change the function defining the indirect effect of X (Equation (4)).

In a *second stage moderated mediation model* (see Figure 1, panel D), the effect of M on Y is specified as moderated by W and estimated with

$$\hat{M} = i_M + aX$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2W + b_3MW.$$

From these two equations, the indirect effect of X on Y is the product of the effect of X on M (a) and the conditional effect of M on Y $(b_1 + b_3W)$,

$$a(b_1 + b_3W) = ab_1 + ab_3W \tag{5}$$

(Edwards & Lambert, 2007; Hayes, 2015; Preacher et al., 2007), which is a linear function of W. As in the first stage model, the inclusion of XW in the model of Y allows the direct effect of X to be linearly moderated by W, though that would not change the function defining the indirect effect of X.

The weights for W in Equations (4) and (5) – a_3b and ab_3 – I call *indices of moderated mediation* (Hayes, 2015). They quantify the relationship between moderator W and the size of the indirect effect of X on Y through M. Rather than testing a moderated mediation hypothesis with a hypothesis test for interaction for the moderated path combined with a hypothesis test for the unmoderated path (a_3 and b in the first stage model; a and b_3 in the second stage model), Hayes (2015) recommends a bootstrap confidence interval (CI) for the index of moderated mediation, as this index directly quantifies the relationship between the indirect effect and the moderator. Since its publication, this index approach to testing a moderated mediation hypothesis has become popular, with numerous examples in the communication literature and elsewhere (e.g., Goodboy et al., 2016; Johnson, Slater, Silver, & Ewoldsen, 2016; Lee-Won, Abo, Kilhoe, & White, 2016; Lu & Myrick, 2016).

But there are at least two limitations to this approach. First, it cannot be used when a single continuous variable is specified as moderating both the $X \rightarrow M$ and $M \rightarrow Y$ paths. In such a model, the indirect effect is a quadratic function of the moderator (see Hayes, 2015, p. 7), so a moderated mediation hypothesis cannot be reduced to a single test of the product of two regression coefficients. I do not address this limitation here. I instead address a second limitation: It assumes a single moderator variable. This approach to testing a moderated mediation hypothesis has not yet been extended to models with more than one moderator. Yet moderated mediation models with multiple moderators exist in the substantive literature in many fields, including communication. For example, in a health message framing experiment, Krieger and Sarge (2013) examined the effects of self-efficacy on intentions to vaccinate against human papillomavirus (HPV) through perceived response efficacy as a mediator. In one of the models they estimated (see their Figure 4), the effect of response efficacy (the mediator) on vaccination intentions (the dependent variable) was dependent on both perceived susceptibility and perceived severity of the outcomes of HPV. Moreover, Schuck and de Vreese (2012) found that the valence of a news frame (positive versus negative) influenced political participation through perceived risks of the outcome of an upcoming referendum, but this process was dependent on the combination of a participant's attitude toward political organizations and the participant's political efficacy (see their Figure 1).

The added complexity produced by multiple moderators, combined with the lack of treatment of this topic by methodologists, means there is a need for some formal guidance on how to test whether an indirect effect is moderated in models with more than one moderator in the causal system. The remainder of this paper addresses some of these complexities.

Working example

I illustrate computations and implementation using data from a phone survey of residents of the United States. A summary of the methodology and some substantive context of the study is available in Nisbet, Ortiz, Yasamin, and Smith (2011). Participants were asked various questions about national security, terrorism, and their perceptions of various ethnic groups locally and overseas. The survey was in the field in April and May of 2011, and about half way through the data collection, U.S. President Barack Obama announced the killing of Osama bin Laden, the mastermind of the September 2011 terrorist attack on the U.S. Following the announcement, news coverage shifted dramatically for the next days and weeks, with far more frequent and more extensive coverage of terrorism, national security, and the potential consequences of bin Laden's death on safety and future acts of terrorism relative to before the announcement. As participants were randomly assigned to the day they were interviewed, the resulting design is a natural experiment, with 271 respondents contacted after the announcement of bin Laden's death ($X = 1$) and interviewed in a media climate with much heavier coverage or terrorism and national security than the 390 respondents interviewed before the announcement ($X = 0$). This is the independent variable in the analysis, denoted *news content* for convenience in the discussion.[3]

The dependent variable is a measure of support for restriction of the civil liberties of Muslim-Americans (Y), with higher scores reflecting support for such policies as requiring Muslim-Americans to carry identification cards and enhanced government surveillance of mosques. Also measured was respondents' endorsement of various negative stereotypical characteristics of Muslims (e.g., fanatical, dangerous), with higher scores representing a stronger endorsement of negative stereotypes about Muslim-Americans (M). This is used as the mediator in all examples. Thus, the models used as illustrations here propose endorsement of negative stereotypes as the mechanism by which differences in news content following the announcement of the death of bin Laden might affect support for policies to restrict the freedoms of Muslim-Americans living in the U.S. The data also include a measure of the respondents' political conservatism, sex, and age (measured in decades, so 3.0 represents a 30 year old). Age (W) and sex (Z) are used as moderators in all examples, and political conservatism is used as a covariate.

Partial moderated mediation

I first consider models that allow either the $X \rightarrow M$ or $M \rightarrow Y$ path to be *additively* moderated by two variables. Figure 2, panel A, illustrates a *first stage dual moderated mediation model* with two moderators W and Z of the effect of X on M. Figure 2, panel B, depicts a *second stage dual moderated mediation model*, where the effect of M on Y is moderated by W and Z. Some examples of such models hypothesized and tested in the substantive literature include Dixon (2016), Guame et al. (2016), Hill, Billington, and Krägeloh (2014), Schuler, Brandstatter, and Baumann (2013), Suizzo et al. (2012), and Trucco et al. (2011). The dotted arrows in the figure depict that you can but do not have to allow the direct effect of X to be moderated by one or both moderators. Theory or prediction would guide the decision as to which paths are estimated as moderated. The model could also include additional predictors of M and Y as covariates to account for confounding of associations, but such covariates are not denoted in the figure. Moderation of the direct effect and the inclusion of covariates does not affect the mathematics discussed below, and so they are not represented in the equations that follow.

Assuming linear associations between variables, as well as that W and Z (either dichotomous or quantitative and measured at the interval level or higher) linearly moderate the effect of X on Y (i.e., X's effect is a linear function of W and Z), the first stage dual moderated mediation model can be estimated with two equations:

$$\hat{M} = i_M + a_1X + a_2W + a_3Z + a_4XW + a_5XZ \tag{6}$$

$$\hat{Y} = i_Y + c'X + bM. \tag{7}$$

In this model, the effect of X on M ($\theta_{X \rightarrow M}$) is

$$\theta_{X \rightarrow M} = a_1 + a_4W + a_5Z$$

from Equation 6 (see Hayes, 2018) and thus depends on both W and Z, whereas the effect of M on Y is b from Equation (7). Multiplication of these effects yields the indirect effect of X on Y through M:

$$\theta_{X \rightarrow M}b = (a_1 + a_4W + a_5Z)b = a_1b + a_4bW + a_5bZ, \tag{8}$$

which is an additive function of W and Z. In Equation (8), a_1b is the conditional indirect effect of X on Y through M when W and Z are both zero, a_4b quantifies the rate of change in the indirect effect of X as W changes but Z is held constant, and a_5b quantifies the rate of change in the indirect effect of X as Z changes but W is held constant. When a_4b is zero, the indirect effect of X is linearly independent of W when Z is held fixed, and when a_5b is zero, the indirect effect of X is linearly independent of Z when W is held fixed. As ordinary *partial* regression coefficients quantify the relationship between a predictor and the dependent variable when other predictors are held constant, I call a_4b and a_5b indices of *partial moderated mediation* of X's indirect effect by W and Z, respectively. These quantify the relationship between one moderator and the size of X's indirect effect on Y through M when the second moderator is held constant. Partial moderated mediation should not

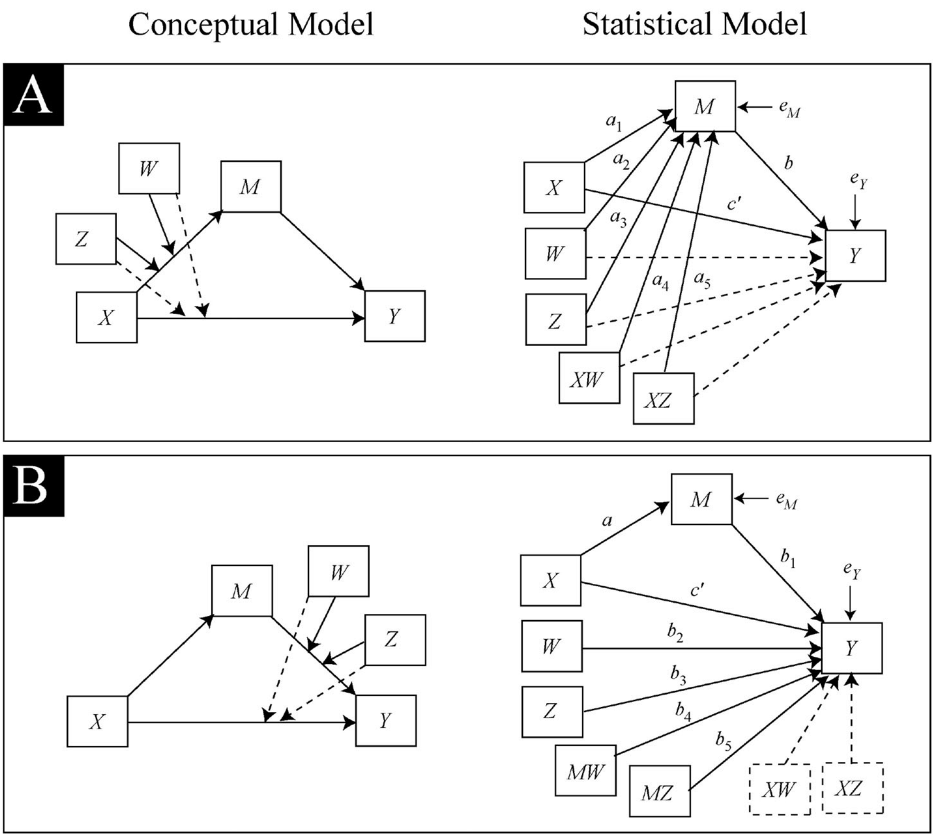

Figure 2. First stage (panel A) and second stage (panel B) additive dual moderated mediation models in conceptual and statistical (path diagram) form. Moderation of the direct effect of *X*, denoted by the dotted arrows, is optional.

be confused with the often-used term "partial mediation," a historically important but now outdated concept that applies to mediation models without moderators (see e.g., Hayes, 2018).

The second stage dual moderated mediation model allows the effect of M on Y to be moderated by two moderators. Making the same assumptions as in the first stage model, though in this case that M's effect on Y is a linear function of W and Z, it is estimated with the equations

$$\hat{M} = i_M + aX \tag{9}$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2W + b_3Z + b_4MW + b_5MZ. \tag{10}$$

The effect of X on M is unmoderated and estimated with a in Equation (9), and the conditional effect of M on Y is

$$\theta_{M\rightarrow Y} = b_1 + b_4W + b_5Z$$

from Equation (10) and thus varies with both W and Z. Multiplication of these effects yields the indirect effect of X on Y through M:

$$a\theta_{M\to Y} = a(b_1 + b_4W + b_5Z) = ab_1 + ab_4W + ab_5Z, \quad (11)$$

which is a linear function of W and Z. In Equation (11), ab_1 is the conditional indirect effect of X when W and Z are both zero, ab_4 is the index of partial moderated mediation of X's indirect effect on Y by W, and ab_5 is the index of partial moderated mediation of X's indirect effect on Y by Z. These indices quantify the rate of change in the indirect effect of X as one moderator changes but the other is held constant.

Visualization

Equations (8) and (11) relate the indirect effect of X on Y through M to two moderators. These functions describing the relationship between the moderators and the indirect effect of X can be visualized by plugging various values of the two moderators into the function and plotting the value of the indirect effect that results from those combinations. Such a graph will take the form of parallel lines. For example, using Equation (8), if W is on the horizontal axis, the indirect effect is on the vertical axis, and different lines are used for different values of Z, the result will be a set of parallel lines (i.e., with a common slope) linking W to the indirect effect. The slope of these lines is a_4b, the index of partial moderated mediation by W. Swapping the roles of W and Z by placing Z on the horizontal axis and using different lines for different values of W, the result is a set of parallel lines with common slope a_5b, the index of partial moderated mediation by Z. An example of such a visual depiction of the indirect effect is provided later.

A dichotomous moderator

The index of partial moderated mediation is interpreted as how much the indirect effect of X on Y through M changes as that moderator changes by one unit when the other moderator is held fixed. If a moderator is dichotomous, then the index of partial moderated mediation for that moderator may be but is not necessarily equal to the difference between the conditional indirect effects of X in the two groups defined by the dichotomous moderator when the other moderator is held constant. With a dichotomous W as moderator, the difference between the indirect effect of X when $W = w_1$ and the indirect effect of X when $W = w_2$ will be equal to

$$a_4b/(w_2 - w_1)$$

in the first stage dual moderated mediation model, and

$$ab_4/(w_2 - w_1)$$

in the second stage dual moderated mediation model. For instance, if the values of $w_1 = -1$ and $w_2 = 1$ are used to code the two groups, then the index of partial moderated mediation by W is one half of the difference between the two conditional indirect effects when Z is held constant (as $w_2 - w_1 = 2$). I recommend coding a dichotomous moderator such that the two codes used differ by one unit (e.g., w_1 and w_2 equal to 0 and 1, or −0.5 and 0.5, respectively) so that the index of partial moderated mediation corresponds to the difference between the two conditional indirect effects of X when Z is held constant. This is a more convenient interpretation. A similar argument applies to the second stage model.

When the indirect effect is visualized using the method described earlier, and if W is used to denote the two lines in the plot with Z placed on the horizontal axis, then the index of partial moderated mediation by W is the vertical distance between the two parallel lines relating the indirect effect to Z.

Inference

Researchers interested in whether one variable moderates the indirect effect of X independent of moderation by a second variable can answer this question with an inference about the index of partial moderated mediation for the first variable. If this index is not statistically different from zero, then this implies that when the other moderator is held fixed, the indirect effect is unrelated to the size of the first moderator. The index is the product of two regression coefficients, and its sampling distribution is not normal or even symmetrical (Bollen & Stine, 1990; Craig, 1936; Stone & Sobel, 1990). As a result, inferential approaches that rely on the standard error of the index and assume the distribution of the ratio of the index to its standard error takes a particular form (such as the normal or t distribution) are problematic. Alternative methods that do not make assumptions about the sampling distribution of the product of regression coefficients would be preferred. Various alternatives exist (such as Monte Carlo CIs or Bayesian credible intervals, see Hayes, 2018; Preacher & Selig, 2012; Yuan & MacKinnon, 2009), but here I recommend the bootstrap CI, as this method is already widely used in mediation analysis for inference about indirect effects (which are also products of regression coefficients), it is easily applied to this problem, and it is available in some software many researchers are already using.

As the construction of a bootstrap CI for a product of regression coefficients is already well documented in the literature (Hayes, 2018; MacKinnon, 2008; Shrout & Bolger, 2002), I do not elaborate on the mechanics here. Suffice it to say that if a c% bootstrap CI for the index of partial moderated mediation for a given moderator does not contain zero, this is evidence of partial moderated mediation of the indirect effect by that moderator with c% confidence. But if the bootstrap CI includes zero, one cannot definitively rule out no relationship between that moderator and the size of the indirect effect at that level of confidence, or even be reasonably certain of the sign of that association.

An example, with implementation

To illustrate the computation of the index of partial moderated mediation and statistical inference, I consider a model where the effect of news content following the announcement of bin Laden's death (X) on support for the restriction of Muslim-American civil liberties (Y) through stronger endorsement of negative stereotypes about Muslims (M) is estimated as moderated in the first stage by age (W) and sex (Z) of the respondent. This is a first stage dual moderated mediation model, such as depicted in Figure 2, panel A.

Using ordinary least squares regression, the regression coefficients in Equations (6) and (7) were estimated, with political conservatism – ”ideo” in the outputs in the appendices –

included as a covariate but not denoted in these equations. Therefore, all interpretations below include the condition "holding political conservatism constant." Table 1 contains the regression coefficients and standard errors. Notice that negative stereotype endorsement is positively related to support for restriction of Muslim-American civil liberties ($b = 0.496$, $p < .001$, 95% CI = 0.412 to 0.579). In the model of negative stereotype endorsement (M), age (W) significantly moderates the effect of news content on endorsement of negative stereotypes ($a_4 = -0.090$, $p = .022$, 95% CI = −0.167 to −0.013), but sex does not ($a_5 = -0.145$, $p = .260$, 95% CI = −0.398 to 0.108). However, neither a statistically significant relationship between the mediator and outcome nor a significant interaction is required to test moderated mediation using the index approach to inference (see Hayes, 2015, for a discussion). What matters is the weight for the moderators in the function defining the relationship between the indirect effect and those moderators. That is, the relationship between age and the indirect effect of news content and between sex and the indirect effect of news content is not a_4, a_5, or b, but, rather, a_4b and a_5b, the indices of partial moderated mediation by age and sex, respectively. In this example, the indirect effect of news content (X) on support for Muslim-American civil liberties restrictions (Y) through negative stereotype endorsement (M) is, from Equation (8),

$$
\begin{aligned}
(a_1 + a_4W + a_5Z)b &= a_1b + a_4bW + a_5bZ \\
&= (0.649)(0.495) + (-0.090)(0.495)W + (-0.145)(0.495)Z \\
&= 0.321 - 0.045W - 0.072Z.
\end{aligned}
$$

The indices of partial moderated mediation are the weights for W and Z in this equation: $a_4b = -0.045$ and $a_5b = -0.072$, respectively. They quantify the relationship between one moderator and the size of the indirect effect of X on Y through M when the other moderator is held constant.

This equation, which is a model of the indirect effect of X as a function of W and Z, is visualized in Figure 3. The index of partial moderated mediation by age (W) is the slopes of the two lines, and the index of partial moderated mediation by sex (Z) is the gap between the two lines. As can be seen, the indirect effect of news content on support for civil liberties restrictions through negative stereotype endorsement decreases with age, meaning the indirect effect is "smaller" among the older when sex is held constant, with "smaller" defined as to the left on the number line. The indirect effect is also "smaller" among men than women. In this figure, this sex difference in the indirect effect is represented by the gap between the dotted and solid lines.

But this is only a description of the relationship between the indirect effect and these two moderators. Inference about partial moderated mediation comes from a bootstrap CI for these indices, which when estimated using 10,000 bootstrap samples (see Table 1) is −0.086 to −0.006 for age (W) and −0.201 to 0.050 for sex (Z). As the CI for the index of partial moderated mediation by age is entirely below zero, we can conclude that independent of any moderation of the indirect effect of news content by sex, age negatively moderates this indirect effect. This is an inference about the slope of the lines in Figure 3. But as the CI for the index of partial moderated mediation by sex includes zero, we can say that independent of the effect of age on the indirect effect, the evidence does not definitively support a claim that the indirect effect differs between men and women. This is an inference about the gap between the lines in Figure 3.

Table 1. Ordinary least squares regression coefficients (with standard errors) from a first stage dual moderated mediation model using the bin Laden effect data.

		Outcome		
		M: Neg. stereotype		Y: Civil liberties
Constant		1.699 (0.157)		0.620 (0.132)
X: News Content	$a_1 \rightarrow$	0.649 (0.220)	$c' \rightarrow$	−0.011 (0.070)
W: Age	$a_2 \rightarrow$	0.086 (0.025)		
Z: Sex	$a_3 \rightarrow$	0.098 (0.082)		
XW: News Content × Age	$a_4 \rightarrow$	−0.090 (0.039)		
XZ: News Content × Sex	$a_5 \rightarrow$	−0.145 (0.129)		
U: Conservatism		0.130 (0.014)		0.104 (0.017)
M: Neg. stereotype endorsement			$b \rightarrow$	0.495 (0.042)
	R	0.367		0.530

Moderator	Index of partial moderated mediation	95% bootstrap CI[a]
W	$a_4b = -0.045$	−0.086 to −0.006
Z	$a_5b = -0.072$	−0.201 to 0.050

[a]Percentile bootstrap CI based on 10,000 bootstrap samples.

Any statistics program capable of estimating the parameters of a linear model can be used to estimate the two equations representing the first (Equations (6) and (7)) or second (Equations (9) and (10)) stage dual moderated mediation model. Point estimates of the indices of partial moderated mediation can be constructed from the regression coefficients by hand. But inference requires a bit more effort when using ordinary least squares regression. Your preferred program must be able to bootstrap not only the distribution of regression coefficients but *products* of regression coefficients. Most statistical software cannot do this off the shelf. But SPSS and SAS users can use the PROCESS macro (Hayes, 2018), a freely available and widely used computational tool for mediation and moderation analysis downloadable from www.processmacro.org. The PROCESS command for SPSS and SAS that conducts this analysis, along with output from the SPSS version, can be found in Appendix 1. Using two separate OLS regression analyses, PROCESS generates estimates of all the parameters in the model and produces a bootstrap CI for each of the indices of partial moderated mediation. The percentile bootstrap CI from PROCESS are the ones reported in the prior section. It also provides output for probing of the moderation of mediation, the topic of the next section.

Probing partial moderated mediation

In multiple regression analysis, it is common following an affirmative test of moderation to probe the interaction using such methods as the pick-a-point approach (also known as a *simple slopes* or *spotlight analysis*) or the Johnson–Neyman technique (sometimes called a *floodlight analysis*). Preacher et al. (2007) and Hayes (2015) discuss comparable methods for probing moderation of an indirect effect, such as picking values of the moderator representing "low," "moderate," and "high" (if the moderator is a continuous variable), estimating the indirect effect conditioned on those values, and conducting an inference about the conditional indirect effect to determine whether it is different from zero at one, some, or all of those values using a bootstrap CI. Low, moderate, and high can be operationalized in a number of ways, such as various percentiles of the distribution, or

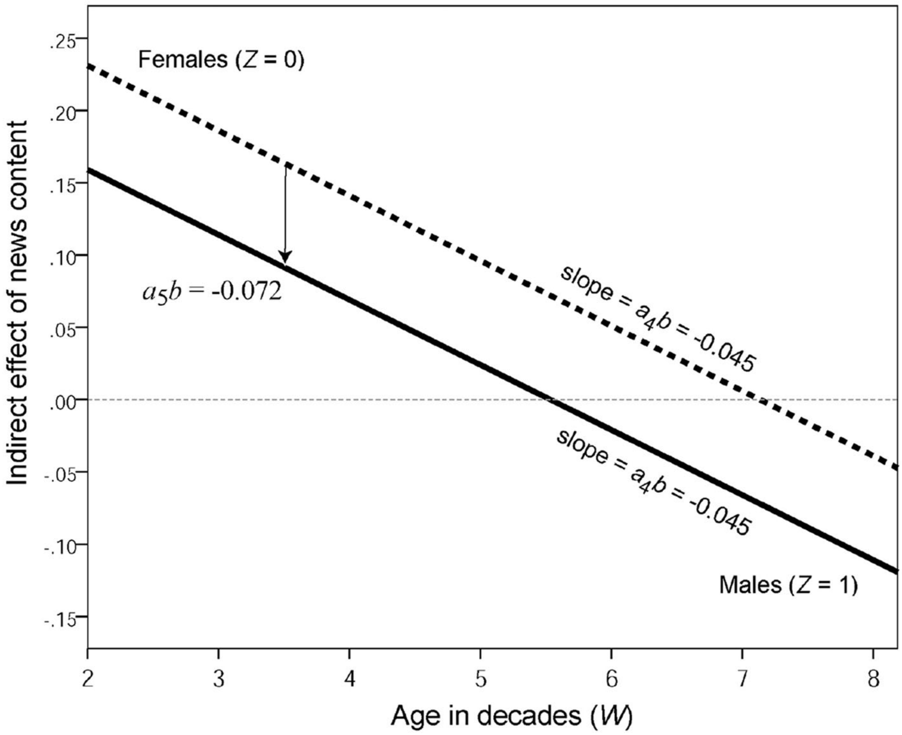

Figure 3. A visual depiction of the indirect effect of news content on support for Muslim-American civil liberties restrictions through negative stereotype endorsement as a function of age (W) and sex (Z). The lines represent the function $a_1b + a_4bW + a_5bZ = 0.321 - 0.045W - 0.072Z$.

using a standard deviation below the mean, the mean, and a standard deviation above the mean. If the moderator is dichotomous, the indirect effects are estimated in each of the two groups.

However, the presence of the second moderator complicates such a procedure applied to probing partial moderated mediation. Unlike in moderated mediation models with a single moderator, because the indirect effect is a function of two moderators, you must choose values for each moderator. There is no way around this, even though the second moderator is held fixed in the test of partial moderated mediation. For example, in the first stage model, from Equation (8), the indirect effect of X is $a_1b + a_4bW + a_5bZ$. You cannot calculate or form an inference about the indirect effect of X when W is some value w without also specifying a value of Z. Likewise, you cannot calculate or conduct an inference about the indirect effect of X when Z is some value z without choosing a value of W.

This means that when probing the moderation of mediation by estimating and applying an inferential test of conditional indirect effects, the results of this probing exercise will likely depend on the chosen value of the second moderator. Absent any guidance dictating the choice for the value of the second moderator, one strategy is to condition the second moderator at its mean. For instance, in the first stage model, if you want to estimate and form an inference about the indirect effect of X when W is “relatively low” – a standard deviation below the mean, for example – calculate

$$a_1 b + a_4 b(\overline{W} - SD_W) + a_5 b\overline{Z}.$$

A bootstrap CI for this quantity that does not include zero is evidence that the indirect effect of X is different for people "relatively low" on W but average on Z. This procedure can be repeated for as many values of W as you choose.

The PROCESS macro generates a table of estimates of the conditional indirect effect of X for various combinations of W and Z as well as bootstrap CI for inference. By default, PROCESS conditions on the 16th, 50th, and 84th percentile of the distribution for continuous moderators or the two values in the data for dichotomous moderators. But the output in Appendix 1 was generated using the *moments* option in PROCESS, which conditions continuous moderators at the mean, a standard deviation below the mean, and a standard deviation above the mean. The result is six conditional indirect effects with bootstrap CIs for men and women "relatively younger" (about 32 years old, or 3.19 decades), "moderate" in age (between 48 and 49 years, or 4.85 decades), and "relatively older" (65 years, or 6.50 decades) as defined by the distribution of age in the data. Using this table, it can be discerned that the estimated indirect effect for women ($Z = 0$) of average age ($W = 4.85$ decades) is 0.105 and statistically significant (95% bootstrap CI = 0.017–0.196), whereas for men ($Z = 1$) of average age, the indirect effect is 0.033 and not definitively different from zero, as the bootstrap CI includes zero (95% bootstrap CI = −0.053 to 0.120). But difference in significance does not imply significantly different, and we already know that these are not statistically different because the difference is the index of partial moderated mediation by sex ($a_5 b = -0.072 = -0.201$ to 0.050) and we concluded earlier that this is not definitively different from zero.

If Z was a continuum, PROCESS would also produce conditional indirect effects of X at values of W when Z is at the mean (when the *moments* option is used) or the median. In this example Z is dichotomous (sex). But it is possible to get PROCESS to estimate indirect effects for participants of "average sex" but of different ages by telling PROCESS to condition Z at 0.522, which is $\bar{Z}$, or the proportion of the sample that is male. This is accomplished by adding "zmodval = 0.522" to the command in Appendix 1. Doing so yields conditional indirect effects of 0.141 (95% CI = 0.057–0.232), 0.067 (95% CI = 0.006–0.130) and −0.007 (95% CI = −0.103–0.087) for the relatively younger, average aged, and relatively older respondents.[4]

Hayes (2015) showed in comparable models with a single moderator that the index of moderated mediation doubles as a test of the difference between any two conditional indirect effects conditioned on two values of the moderator, *regardless* of those two values. A similar argument applies here. Suppose you wanted to know whether the indirect effect of X on Y through M differs when $W = w_1$ compared to when $W = w_2$, conditioned on Z being some value $Z = z$. In the first stage model, this difference is

$$(a_1 + a_4 w_2 + a_5 z)b - (a_1 + a_4 w_1 + a_5 z)b = a_4 b(w_2 - w_1)$$

and in the second stage model, the difference is

$$a(b_1 + b_4 w_2 + b_5 z) - a(b_1 + b_4 w_1 + b_5 z) = ab_4(w_2 - w_1).$$

These are both equal to the index of partial moderated mediation by W multiplied by the difference between the two w values. An inference for this difference using a bootstrap CI is determined entirely by the CI for the index of partial moderated mediation by W because $w_2 - w_1$ is a constant. As $w_2 - w_1$ does not vary between bootstrap samples, it makes no difference what two values of w_1 and w_2 are used in the comparison. If a CI for the index of partial moderated mediation by W includes zero, then no two conditional indirect effects for different values of W when Z is held fixed can be deemed different. But if this CI excludes zero, then any two conditional indirect effects for different values of W, conditioned on the same Z, can be deemed different. This argument applies to the index of partial moderated mediation by Z as well as to the second stage dual moderated mediation model.

Having established that age moderates the indirect effect of news content, we do not need to further test whether the indirect effect of news content differs between (for instance) younger and older respondents of the same sex. The CI for the index of partial moderated mediation by age does not include zero. Therefore, we know the indirect effect of news content differs between respondents of different age but of the same sex.

Conditional and moderated moderated mediation

In the models considered so far, moderation of the indirect effect of X on Y through M by one moderator is fixed to be independent of the second moderator. I next address models in which the moderation of the indirect effect by one variable is dependent on the second moderator – *moderated moderated mediation*. This can occur in models with a three-way interaction involving either X or M and two moderators W and Z (as in Krieger & Sarge, 2013, described earlier). Later I show how moderated moderated mediation is also the result when one variable moderates the $X \rightarrow M$ path and a second variable moderates the $M \rightarrow Y$ path.

Consider a *first stage moderated moderated mediation model*, depicted in Figure 4, panel A. Examples of this model in the substantive literature include Gabbiadini, Riva, Andrighetto, Volpato, and Bushman (2016), Lange, Corbett, Lippke, Knoll, and Schwarzer (2015) and Vantilborgh et al. (2013). This model is represented with two equations:

$$\hat{M} = i_M + a_1X + a_2W + a_3Z + a_4XW + a_5XZ + a_6WZ + a_7XWZ \tag{12}$$

$$\hat{Y} = i_Y + c'X + bM. \tag{13}$$

From Equation (12), the effect of X on M is

$$\theta_{X \rightarrow M} = a_1 + a_4W + a_5Z + a_7WZ,$$

(see Hayes, 2018) and thus depends on both W and Z, whereas the effect of M on Y is b from Equation (13). Additional variables could be added as covariates to these equations, and one could also allow the direct effect to be moderated by W, Z, or both, as depicted in Figure 4, panel A. Doing so does not alter the derivations described below.

Multiplication of the effect of X on M and the effect of M on Y yields the indirect effect of X on Y through M:

$$\theta_{X \rightarrow M}b = (a_1 + a_4W + a_5Z + a_7WZ)b = a_1b + a_4bW + a_5bZ + a_7bWZ, \tag{14}$$

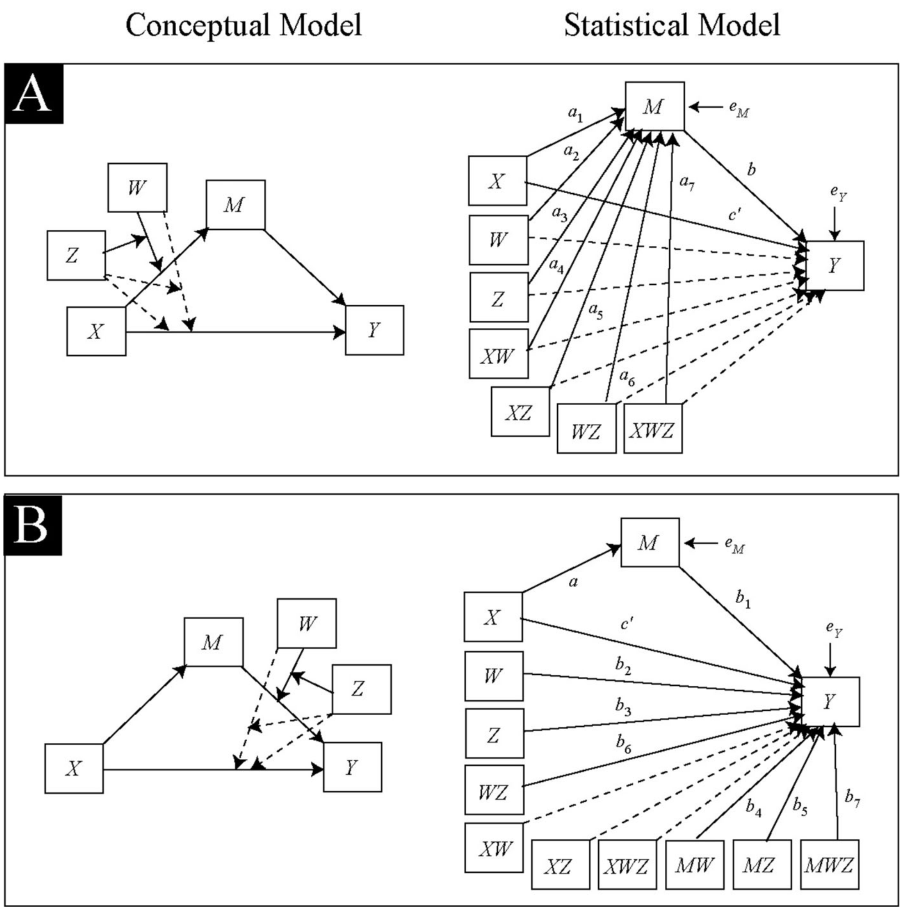

Figure 4. First stage (panel A) and second stage (panel B) moderated moderated mediation models in conceptual and statistical (path diagram) form. Moderation of the direct effect of *X*, denoted by the dotted arrows, is optional.

which is a function of *W*, *Z*, and their product. Plugging in values of *W* and *Z* into Equation (14) results in the indirect effect of *X* on *Y* conditioned on those values of *W* and *Z*. The relationship between the indirect effect of *X* and the moderators *W* and *Z* can be visualized by substituting estimates of a_1, a_4, a_5, a_7, and b into Equation 14 and plotting the resulting values for various values of *W* and *Z* in the range of the data.

Some algebra shows that Equation (14) can be written in an equivalent form as

$$\theta_{X\rightarrow M}b = a_1b + (a_4b + a_7bZ)W + a_5bZ, \tag{15}$$

which means that the relationship between *W* and the indirect effect of *X* is a linear function of *Z*: $a_4b + a_7bZ$. If one were to plot the relationship between *W* and the indirect effect of *X* in two-dimensional space, with *W* on the horizontal axis, the result would be a set of lines for different values of *Z*, and the slope of the line relating *W* to the indirect effect of *X* when $Z = z$ would be $a_4b + a_7bz$. Thus, $a_4b + a_7bZ$ in Equation (15) quantifies the rate of change of the indirect effect of *X* on *Y* as *W* is changing, conditioned on a specific value of *Z*. That is, it quantifies moderation of the indirect effect of *X* by *W* at a given value of *Z*.

Accordingly, I call $a_4b + a_7bZ$ the *index of conditional moderated mediation* by W for this model. If the index of conditional moderated mediation by W at a specific value of Z is statistically different from zero, then this implies that W moderates the size of the indirect effect of X at that value of Z. If W is dichotomous with the groups coded by values that differ by one unit, then the index of conditional moderated mediation by W quantifies the difference between the conditional indirect effect of X for the two groups conditioned on that value of Z. If Z is dichotomous with groups coded with a one unit difference, the index of conditional moderated mediation by W quantifies the difference between the slopes of the line relating W to the indirect effect of X for the two groups coded with Z. A bootstrap CI for the index of conditional moderated mediation by W can be used for inference without making any assumptions about the shape of the sampling distribution of the index.

If you are interested in testing whether the moderation of the indirect effect of X by W varies with Z, a "pick-a-point" type procedure as just described could be used by choosing different values of Z and testing whether the index of conditional moderated mediation by W is different from zero using a bootstrap CI. With a set of inferences about whether or not the indirect effect is moderated by W for certain values of Z, an argument can be pieced together about the nature of the moderation of the moderation of the indirect effect by the pattern of inferences for the values of Z chosen.

But this is not the procedure I recommend. As in ordinary moderation analysis, it makes more sense to first determine if an effect is moderated before probing that moderation. In this case, we are interested in if the moderation of the indirect effect of X by W is moderated by Z. In the first stage moderated moderated mediation model, a_7b quantifies the moderation by Z of the moderation of the indirect effect of X by W. This is apparent by recognizing that in $(a_4b + a_7bZ)W$, a_7b quantifies the relationship between Z and the moderation of the indirect effect of X by W. In this function, a_4b estimates how the indirect effect of X varies with W when $Z = 0$, and a_7b quantifies how that moderation of the indirect effect of X by W changes as Z changes. Thus, a_7b quantifies the rate of change in the moderation of the indirect effect of X by W as Z is changing. In a plot of the indirect effect of X as a function of W and Z, a_7b corresponds to the rate of change in the slope of the line relating W to the indirect effect of X as Z changes. It is an *index of moderated moderated mediation.* If a_7b is zero, then Z does not moderate the moderation of the indirect effect of X by W. In this plot of the indirect effect, such a phenomenon would take the form of a set of parallel lines relating W to the indirect effect of X at various values of Z (as in, for example, Figure 3). But if a_7b is different from zero, then these lines would not be parallel, meaning that change in the indirect effect of X as W changes depends on Z.

An inference about the index of moderated moderated mediation is an inference about whether the moderation of the indirect effect of X on Y by W is moderated by Z. A bootstrap CI for the index is a sensible inferential tool. If a CI for the index of moderated moderated mediation contains zero, then you cannot definitively claim that Z moderates the moderation of the indirect effect of X by W. But if the CI does not contain zero, this is evidence of *moderated moderated mediation.* With affirmative evidence, it *then* makes sense to probe this moderation of moderated mediation by choosing values of Z and testing whether the indirect effect of X is moderated by W at those chosen values of Z, using the index of conditional moderated mediation and corresponding inference described earlier. Without such affirmative evidence, there would be no need to engage in this probing exercise, as the evidence does not support the conclusion that the moderation of the indirect effect varies as a function of the second moderator.

There is a symmetry to moderated moderated mediation, just as there is in interactions in regression analysis. In this model, as discussed thus far, W serves the role of *primary moderator* and Z is the *secondary moderator*. As the model is diagrammed in Figure 4, panel A, W moderates the effect of X on M, and Z moderates the extent of this moderation. Equation (15) makes this mathematically explicit, with its representation of the indirect of X on Y through M as a linear function of W, with the weight for W in this function being determined by Z. The weight for Z in this function defining the moderation of the indirect effect by W, a_7b, is the index of moderated moderated mediation. But Equation (14) can be written in an alternative form

$$\theta_{X \to M} b = a_1 b = a_1 b + (a_5 b + a_7 b W) Z + a_4 b W. \tag{16}$$

In this form, Z is the primary moderator, W is the secondary moderator, and $a_5b + a_7bW$ is the index of conditional moderated mediation by Z. It quantifies the moderation of the indirect effect of X by Z conditioned on a value of W, and a_7b quantifies the moderation by W of the moderation of the indirect effect of X by Z. So a_7b is symmetrical in interpretation with respect to whether W or Z is the primary or secondary moderator. If a_7b, the index of moderated moderated mediation, does not equal equal zero, it can be said that W moderates the moderation of the indirect effect of X by Z or that Z moderates the moderation of the indirect effect of X by W.

When the moderation of moderated mediation occurs in the second stage of the mediation process, the result is a *second stage moderated moderated mediation model*, as in Figure 4, panel B. Examples of such a model in the substantive literature include Freis, Brown, Carroll, and Arkin (2015), Kingsbury, Coplan, and Rose-Krasnor (2013), and Krieger and Sarge (2013). This model is represented with two equations:

$$\hat{M} = i_M + aX \tag{17}$$

$$\hat{Y} = i_Y + c_1' X + b_1 M + b_2 W + b_3 Z + b_4 MW + b_5 MZ + b_6 WZ + b_7 MWZ. \tag{18}$$

From Equation (17), the effect of X on M is a and from Equation (18), the effect of M on Y is

$$\theta_{M \to Y} = b_1 + b_4 W + b_5 Z + b_7 WZ.$$

The indirect effect of X is the product of these two effects

$$a\theta_{M \to Y} = a(b_1 + b_4 W + b_5 Z + b_7 WZ) = ab_1 + ab_4 W + ab_5 Z + ab_7 WZ.$$

Derivations that follow the same logic as for the first stage moderated moderated mediation model apply. With W as the primary moderator (as in Figure 4, panel B), the index of conditional moderated mediation by W is $ab_4 + ab_7Z$. If Z is the primary moderator, the index of conditional moderated mediation by Z is $ab_5 + ab_7W$. In both cases, the index of moderated moderated mediation is ab_7. An inference that the index of moderated moderation mediation is different from zero leads to the claim that the moderation by W of the indirect effect of X depends on Z, and the moderation by Z of the indirect effect of X depends on W. Such moderation of moderated mediation can then be probed by conducting an inference about the index of conditional moderated mediation by W at various values of Z or the index of conditional moderated mediation by Z at various values of W, and substantively interpreting the pattern of inferences.

Illustration and implementation

To illustrate the computation and interpretation of these indices, I modify the earlier example by allowing sex to moderate the moderation by age of the effect of news content on negative stereotype endorsement. That is, rather than two two-way interactions between news content and the two moderators in the first stage example from earlier, this model allows for a three-way interaction between news content, age, and sex in the model of negative stereotype endorsement, with age as the primary moderator W and sex as the secondary moderator Z. Of course, all lower order products are also included in this model. Thus, this is a first stage moderated moderated mediation model as in Figure 4, panel A.

The regression coefficients for the models of stereotype endorsement (M) and support for Muslim-American civil liberties restrictions (Y) can be found in Table 2, which was produced from the PROCESS output in Appendix 2. Because the model of Y is the same as for the second stage dual moderated mediation model, the regression coefficients in the Y model are the same and reflect that stereotype endorsement is positively related to support for restriction of Muslim-American civil liberties ($b = 0.496$, $p < .001$, 95% CI = 0.412–0.579). In the model of stereotype endorsement, there is a three-way interaction between news content, age, and sex. Probing this interaction reveals that age moderates the effect of news content on stereotype endorsement among women but not men. Young to average-aged women interviewed later more strongly endorsed negative stereotypes about Muslim-Americans than did comparably aged women interviewed earlier. No

Table 2. Ordinary least squares regression coefficients (with standard errors) from a first stage moderated moderated mediation model using the bin Laden effect data.

		Outcome		
		M: Neg. stereotype		*Y*: Civil liberties
Constant		1.646 (0.197)		0.620 (0.132)
X: News Content	$a_1 \rightarrow$	1.137 (0.300)	$c' \rightarrow$	−0.011 (0.070)
W: Age	$a_2 \rightarrow$	0.099 (0.034)		
Z: Sex	$a_3 \rightarrow$	0.224 (0.251)		
XW: News Content × Age	$a_4 \rightarrow$	−0.186 (0.056)		
XZ: News Content × Sex	$a_5 \rightarrow$	−1.040 (0.401)		
WZ: Age × Sex	$a_6 \rightarrow$	−0.026 (0.049)		
XWZ: News Content × Age × Sex	$a_7 \rightarrow$	0.184 (0.078)		
U: Conservatism		0.128 (0.014)		0.104 (0.017)
M: Neg. stereotype endorsement			$b \rightarrow$	0.495 (0.042)
	R	0.379		0.530
			Index	95% bootstrap CI[a]
Moderated moderated mediation			0.091	0.014–0.174
Conditional moderated mediation				
by age (*W*) among	Females ($Z = 0$)		−0.092	−0.156 to −0.034
	Males ($Z = 1$)		−0.001	−0.053 to 0.052
by sex (*Z*) among	Younger ($W = 3.191$)		−0.224	−0.406 to −0.059
	Average age ($W = 4.8460$)		−0.074	−0.202 to 0.048
	Older ($W = 6.505$)		0.077	−0.108 to 0.267

[a]Percentile bootstrap CI based on 10,000 bootstrap samples.

such effect is observed for older women. But age was unrelated to the size of the effect of news content on negative stereotype endorsement among men. Indeed, among men, regardless of age, stereotype endorsement was no different on average among those interviewed after the announcement of bin Laden's death than those interviewed before.

However, these findings reflect just the first stage of the mediation process. They do not quantify the indirect effect of news content or how that indirect effect is moderated by age and sex. From Equation (14), and substituting estimated regression coefficients where appropriate, the indirect effect of news content on support for Muslim-American civil liberties restrictions through negative stereotype endorsement depends on age (W), sex (Z), and their product

$$\begin{aligned}(a_1 + a_4W + a_5Z + a_7WZ)b &= a_1b + a_4bW + a_5bZ + a_7bWZ \\ &= (1.137)(0.495) + (-0.186)(0.495)W \\ &\quad + (-1.040)(0.495)Z + (0.184)(0.495)WZ \\ &= 0.563 - 0.092W - 0.515Z + 0.091WZ.\end{aligned}$$

This function is depicted in Figure 5. As can be seen, among women, the relationship between age and the size of the indirect effect of news content is negative, but among men there appears to be no relationship between age and the size of the indirect effect.

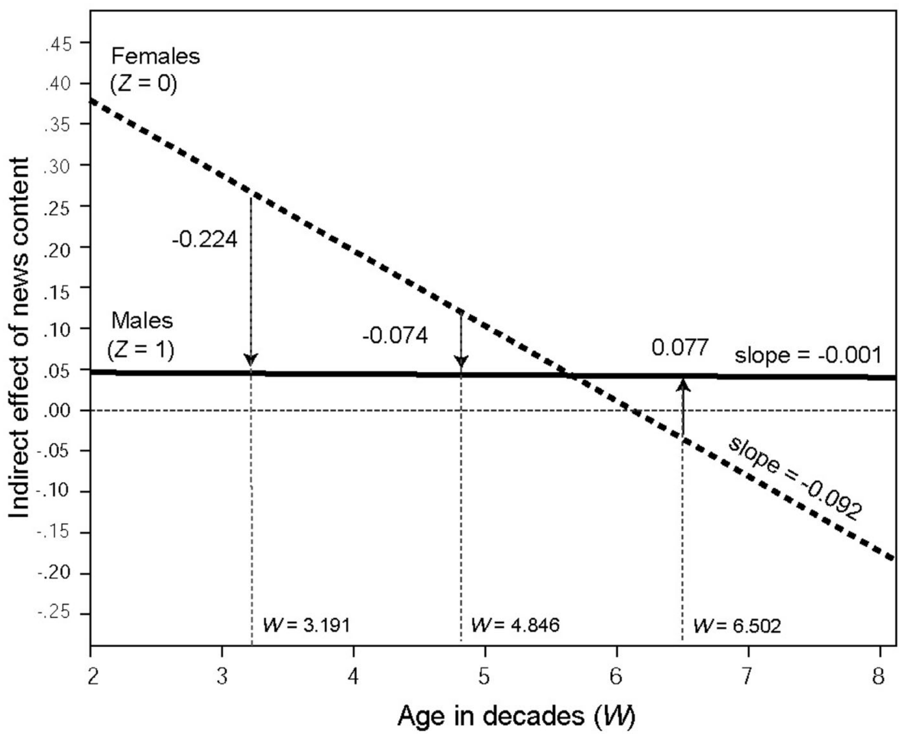

Figure 5. A visual depiction of the indirect effect of news content on support for Muslim-American civil liberties restrictions through negative stereotype endorsement as a function of age (W) and sex (Z). The lines represent the function $a_1b + a_4bW + a_5bZ + a_7bWZ = 0.563 - 0.092W - 0.515Z + 0.091WZ$.

Alternatively, as is apparent in Figure 5, the sex difference in the indirect effect of news content appears to vary with age.

Both of these interpretations reflect *moderated moderation mediation* – the moderation of the indirect effect of news content by one moderator depends on the other moderator. The index of moderated moderated mediation quantifies this, and an inference about its value can be used as a test of moderated moderated mediation. In this model, the index of moderated moderated mediation is $a_7b = 0.184(0.495) = 0.091$, with a 95% bootstrap CI that is entirely above zero (0.014 to 0.174; see the PROCESS macro output in Appendix 2). Consequently, we can say that the moderation of the indirect effect by age differs between men and women. Indeed, observe that 0.091 is the difference between the slopes of the two lines relating age to the size of the indirect effect in Figure 5. We see next that these two slopes are the indices of conditional moderated mediation by age, one for males and one for females.

The moderation of moderated mediation revealed by this analysis can be probed by choosing values of one moderator and estimating the moderation of the indirect effect of news content by the other – the index of conditional moderated mediation – and conducting an inference about this conditional moderated mediation. For example, from Equation (15) and substituting the regression coefficients from the analysis, among women ($Z = 0$), the indirect effect of news content changes by

$$a_4b + a_7bZ = -0.092 + 0.091(0) = -0.092$$

as age (W) changes by 1 unit (10 years). This is the index of conditional moderated mediation by age among women, and the slope of the line for women in Figure 5. A bootstrap CI for this index is −0.156 to −0.034 (see the PROCESS output in Appendix 2). Therefore, we can say that age negatively moderates the indirect effect of news content among women. But among men, the indirect effect of news content changes by only

$$a_4b + a_7bZ = -0.092 + 0.091(1) = -0.001$$

as age changes by one unit. This is the index of conditional moderated mediation by age among men and the slope of the line for men in Figure 5. A 95% bootstrap CI includes zero (−0.053 to 0.052; see the PROCESS output in Appendix 2), so we cannot conclude definitively that age moderates the indirect effect of news content among men.

As discussed previously, the index of conditional moderated mediation can be constructed for each moderator. Thus, we could also probe the moderation of moderated mediation by choosing values of age and then estimating the index of conditional moderated mediation of the indirect effect of news content by sex and a CI for inference at these values of age. The index of conditional moderated mediation by sex is, from Equation (16),

$$a_5b + a_7bW = -0.515 + 0.091W,$$

which for values of age corresponding to relatively young ($W = 3.191$), average ($W = 4.846$), and older ($W = 6.502$) in age are −0.224, −0.074, and 0.077. In Figure 5, these are the distances between the solid and dotted lines conditioned at these three values of age. These are not found in the PROCESS output in Appendix 2, as PROCESS treats W (age in this example) as the primary moderator. But the command at the end of the Appendix 2 flips the roles of sex and age, making sex the primary moderator. Doing so produces the indices of conditional moderated mediation just described, and a 95% CI for the index of conditional moderated mediation by sex excludes zero only among the younger (−0.406 to −0.059). Thus, the indirect effect of news content differs between men and women who are younger but not among the average or older in age.

When the moderators are split between stages of the mediation process

In the examples considered thus far, the two moderators were located on either the first or the second stage of the mediation process. An alternative model locates one moderator in the first stage and one on the second stage, as depicted in Figure 6. Examples of such a model theorized in the substantive literature include Armstrong et al. (2014), Laran et al. (2011), and Li et al. (2015). While conceptually and substantively a different model, this *first and second stage dual moderated mediation model* nevertheless has mathematical similarities to both the first and the second stage moderated moderated mediation model, in that the indirect effect is a function of W, Z, and their product. Furthermore, the relationship between one moderator and the indirect effect of X on Y through M is conditioned on the other moderator.

The equations specifying this model are

$$\hat{M} = i_M + a_1X + a_2W + a_3XW \tag{19}$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2Z + b_3MZ. \tag{20}$$

From Equation 19, the effect of X on M is

$$\theta_{X\to M} = a_1 + a_3W,$$

and from Equation 20, the effect of M on Y is

$$\theta_{M\to Y} = b_1 + b_3Z.$$

The indirect effect of X on Y through M is the product of these effects:

$$\theta_{X\to M}\theta_{M\to Y} = (a_1 + a_3W)(b_1 + b_3Z) = a_1b_1 + a_3b_1W + a_1b_3Z + a_3b_3WZ \tag{21}$$

(see Preacher et al., 2007) and a function of W, Z, and their product, just as in the first or second stage moderated moderated mediation model. Rewriting Equation (21) as

$$\theta_{X\to M}\theta_{M\to Y} = a_1b_1 + (a_3b_1 + a_3b_3Z)W + a_1b_3Z,$$

shows that the relationship between W and the indirect effect of X is a linear function of Z, $a_3b_1 + a_3b_3Z$, which is the index of conditional moderated mediation by W for this model. It quantifies the relationship between W and the size of the indirect effect of X conditioned on Z.

Equation (21) can also be written as

$$\theta_{X\to M}\theta_{M\to Y} = a_1b_1 + a_3b_1W + (a_1b_3 + a_3b_3W)Z,$$

which shows that the relationship between Z and the indirect effect of X is a linear function of W. This linear function, $a_1b_3 + a_3b_3W$, is the index of conditional moderated mediation by Z and quantifies the relationship between Z and the size of the indirect effect of X conditioned on W. Finally, notice that the indices of conditional moderated mediation share

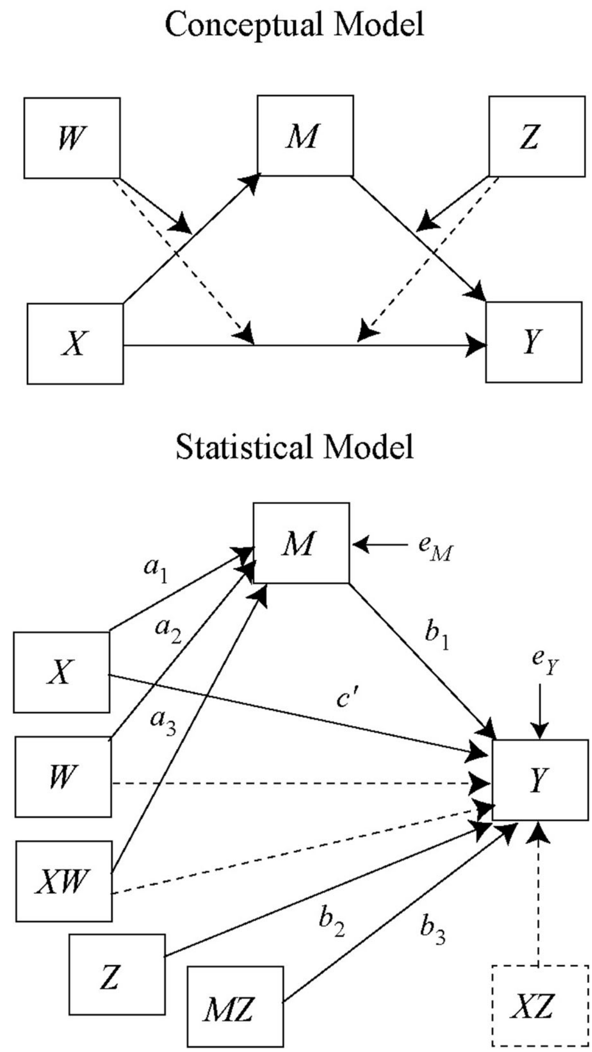

Figure 6. A first and second stage dual moderated mediation model.

a_3b_3 as the weight for the second moderator. This is the index of moderated moderated mediation for this model and quantifies the rate of change in the moderation by W of the indirect effect of X as Z changes, as well as the rate of change in the moderation by Z of the indirect effect of X as W changes.

The analysis of such a model can proceed just as described for the first stage or second stage moderated moderated mediation model. First test whether the moderation of the indirect effect by one moderator is itself moderated by the other moderator. This question can be answered with a bootstrap CI for the index of moderated moderated mediation. With affirmative evidence, you then probe this moderation of moderated mediation by estimating and conducting an inference for the index of conditional moderated mediation for various values of the second moderator and piecing together a substantive interpretation for the pattern of results. With no affirmative evidence of moderated moderated mediation, no probing is required.

I do not work through a complete example of this model, but in Appendix 3 I provide PROCESS output for this model using the same data set. In this model, age is the first stage moderator of the effect of news content on stereotype endorsement, and sex is the second stage moderator of the effect of negative stereotype endorsement on support for restriction of Muslim-American civil liberties. This output was used to generate Table 3. As can be seen, contrary to the first stage moderated moderated mediation model, here we do not have definitive support for moderated moderated mediation. Examining the indices of conditional moderated mediation, it appears that the indirect effect of news content is negatively related to age in both women (−0.045) and men (−0.038), with bootstrap CIs that are entirely negative. The difference between these is 0.007, the index of moderated moderated mediation, but a 95% bootstrap CI includes zero (−0.006 to 0.027), meaning that the moderation of the indirect effect of news content by age does not differ between men and women. Though not shown in the PROCESS output in Appendix 3, modifying the code as described at the end of this appendix reprograms this model so that W rather than Z is the moderator of the $M \rightarrow Y$ path. This is necessary because PROCESS generates the index of conditional moderated mediation by W at values of Z, not the index of conditional moderated mediation by Z at values of W. Executing the command shows there are no sex differences in the size of the indirect effect of news content among younger, average, or older respondents, as the CIs for the index of conditional moderated mediation by sex includes zero at these three values of age (see Table 3).

An important lesson from this difference in findings relative to the prior examples is that the results you get about the moderation of an indirect effect will be dependent on where you decide to place the moderators in the mediation process. Ideally, these decisions

Table 3. Ordinary least squares regression coefficients (with standard errors) from a first and second stage dual moderated mediation model using the bin Laden effect data.

		Outcome		
		M: Neg. stereotype		*Y*: Civil liberties
Constant		1.771 (0.144)		0.518 (0.180)
X: News Content	$a_1 \rightarrow$	0.541 (0.198)	$c' \rightarrow$	−0.013 (0.070)
W: Age	$a_2 \rightarrow$	0.082 (0.024)		
Z: Sex			$b_2 \rightarrow$	0.205 (0.242)
XW: News Content × Age	$a_3 \rightarrow$	−0.084 (0.039)		
MZ: Neg stereo. endorsement × Sex			$b_3 \rightarrow$	−0.083 (0.080)
U: Conservatism		0.130 (0.014)		0.104 (0.017)
M: Neg. stereotype endorsement			$b_1 \rightarrow$	0.538 (0.059)
	R	0.364		0.532
			Index	95% bootstrap CI[a]
Moderated moderated mediation			0.007	−0.006 to 0.027
Conditional moderated mediation				
By age (*W*) among	Females ($Z = 0$)		−0.045	−0.091 to −0.003
	Males ($Z = 1$)		−0.038	−0.076 to −0.003
By sex (*Z*) among	Younger ($W = 3.191$)		−0.023	−0.077 to 0.020
	Average age ($W = 4.8460$)		−0.011	−0.041 to 0.011
	Older ($W = 6.505$)		0.000	−0.021 to 0.026

[a]Percentile bootstrap CI based on 10,000 bootstrap samples.

about model construction are informed by theory, research, and a priori hypothesis rather than by post hoc data exploration. If you decide to try different possibilities to see what results are interesting and interpretable, it is a good idea to attempt to replicate in a new sample or in a holdout sample from the original dataset. Such exploratory data mining tends to capitalize on chance and can result in overfitting of the data. Replication of results is the best insurance against this.

Conclusion (with some further extensions)

In this paper, I introduced the concepts of partial, conditional, and moderated moderated mediation. W partially moderates the mediation of X's effect on Y through M if the size of the indirect effect of X is related to W when a second moderator Z is held constant. W conditionally moderates the mediation of X's indirect effect if the indirect effect is related to W conditioned on a specific value of Z. And the moderation of X's indirect effect by W is itself moderated by Z – moderated moderated mediation – if Z is related to the rate of change of the indirect effect of X as W changes. In the spirit of the index approach introduced by Hayes (2015), I derived indices of partial, conditional, and moderated moderated mediation and recommend the use of a bootstrap CI for hypothesis testing. I conclude with a few additional extensions.

More than one mediator

My discussion has assumed a single mediator. But the mathematics applies to models with more than one mediator operating in parallel or in serial (for a discussion of the parallel and serial multiple mediator model, see Preacher & Hayes, 2008; Hayes, 2018; MacKinnon, 2008). For instance, in a model with k parallel mediators, there are k models of M, one for each of the k mediators, and $k + 1$ partial regression coefficients in the model of Y, one for each M and one for X. The indices of partial, conditional, and moderated moderated mediation for a specific mediator are calculated as in the discussion above but using the regression coefficients corresponding to mediator M in the computations. The PROCESS macro can estimate conditional process models with multiple mediators specified in parallel or in serial (as of version 3) and provides the indices of partial, conditional, and moderated moderated mediation by each moderator for each mediator, along with bootstrap CIs for inference.

Multicategorical causes and moderators

This treatment of partial, moderated, and conditional moderated mediation has assumed dichotomous or continuous causes (X) and/or moderators (W and Z). The ideas and underlying mathematics are easily generalized to multicategorical variables, though the specifics are beyond the scope of this article. Hayes and Preacher (2014) discuss mediation analysis with a multicategorical X, and Hayes and Montoya (2017) provide a tutorial on moderation analysis when one of the variables (moderator or independent variable) is multicategorical and the other is continuous or dichotomous. In the case of multicategorical X with k categories, there are $k - 1$ relative indirect effects that are coding dependent and that can be moderated partially or conditionally. When a moderator is multicategorical, moderation is expressed in terms of how an indirect effect varies in one category of the moderator relative to some reference categories or set of categories. Although the underlying mathematics is more complicated, PROCESS v3 accepts multicategorical independent variables and moderators, does all the required computations, and produces indices of conditional, partial, and moderated moderated mediation.

Alternatives to regression-based estimation

Inference about partial, conditional, or moderated moderated mediation requires the integration of at least two regression coefficients across two regressions models, one for M and one for Y. The PROCESS macro described earlier facilitates this integration by estimating the models separately and then combining the information from the two models, while also offering bootstrap inference. Simultaneous estimation of the models of M and Y can also be undertaken using maximum likelihood methods in SEM software, so long as that software allows for the estimation of new parameters formed as products of model coefficients (such as Mplus does). In a model with only observed variables, the results will generally be the same as when using separate regression analyses (Hayes, Montoya, & Rockwood, 2017).

Latent variables

My discussion and example applications have been based on regression analysis of models of observed variables. This approach has all the weaknesses of any regression analysis when variables are measured with error, as they often are in practice. Such weaknesses, relative to the use of latent variable modeling using SEM, include reduced precision in the estimation of model parameters and, in some circumstances, bias in the estimation of those parameters resulting from random measurement error (Cheung & Lau, 2015).

Models that integrate moderation and mediation can be estimated using latent variables in an SEM framework (see Hayes & Preacher, 2013; Sardeshmukh & Vandenberg, 2017). The approach I describe for assessing partial, conditional, and moderated moderation mediation generalizes to latent variable models or models that blend latent and observed variables. The indices are formed as function of weights in the structural model linking variables whether latent or observed. In principle, bootstrap CIs for these indices can be constructed for inference, although some SEM programs do not have features for bootstrapping functions of structural parameters (Mplus and the lavaan package for R are two exceptions that do). Conditional process analysis can be especially difficult when the model includes interactions between latent variables, as would often be the case in application. In that case, other inferential methods could be used instead, such as a Monte Carlo CI (see Hayes & Preacher, 2013).

Notes

1. Preacher et al. (2007) discuss moderation of an indirect effect when two variables moderate separate paths in the causal system, and Hayes and Preacher (2013) illustrate conditional process analysis in a model with three moderators. But neither of these directly address the kinds of questions that are the focus of this paper.
2. To simplify the discussion, I do not distinguish between parameters and estimates of those parameters in my notation. Thus, symbols such as a, b, or c' could refer to an unknown

parameter or estimate of that parameter based on data available. When the distinction is important, I will verbally rather than symbolically distinguish between them.

3. Of course, more than just news content is "manipulated" in this natural experiment. For example, perhaps those interviewed after his death were talking more about terrorism with neighbors and friends than those interviewed before his death.
4. When conditioning on "average sex," these indirect effects conditioned on age are sex-weighted average conditional indirect effects, with the estimates weighted more heavily toward the conditional indirect effect among men because there are more men in the sample. One could condition at $Z = 0.50$, which would generate sex-unweighted average conditional indirect effects.

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Appendices

Appendix 1

PROCESS code and output for a first stage dual moderated mediation model. Only PROCESS version 3 code out and output is provided here. For version 2, see the supplementary materials available at www.afhayes.com and www.processmacro.org

SPSS:
```
process y=mcivil/x=binladen/m=stereo/w=age/z=sex/cov=ideo
    plot=1/moments=1/model=9/boot=10000.
```
SAS:
```
%process (data=binladen,y=mcivil,x=binladen,m=stereo,w=age,
    z=sex,cov=ideo,plot=1,moments=1,model=9,boot=10000);
```

```
************ PROCESS Procedure for SPSS Release 3.00 ***************

Model :  9
    Y :  mcivil
    X :  binladen
    M :  stereo
    W :  age
    Z :  sex

Covariates:
 ideo

Sample
Size: 661

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

OUTCOME VARIABLE:
    stereo

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3666      .1344      .6457    16.9231     6.0000   654.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.6990      .1565    10.8555      .0000     1.3917     2.0063
binladen      .6489      .2202     2.9470      .0033      .2165     1.0813
age           .0857      .0246     3.4916      .0005      .0375      .1340
Int_1        -.0902      .0391    -2.3049      .0215     -.1671     -.0134
sex           .0980      .0823     1.1901      .2344     -.0637      .2596
Int_2        -.1453      .1288    -1.1282      .2597     -.3981      .1076
ideo          .1300      .0143     9.1212      .0000      .1020      .1580

Product terms key:
 Int_1    :        binladen x        age
 Int_2    :        binladen x        sex

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0070     5.3125     1.0000   654.0000      .0215
X*Z      .0017     1.2728     1.0000   654.0000      .2597
```

```
----------
Focal predict: binladen (X)
      Mod var: age      (W)
      Mod var: sex      (Z)

Conditional effects of the focal predictor at values of moderator(s):

   age       sex    Effect      se         t        p      LLCI     ULCI
3.1905     .0000     .3611   .1188    3.0386    .0025     .1277    .5944
3.1905    1.0000     .2158   .1040    2.0752    .0384     .0116    .4201
4.8460     .0000     .2117   .0926    2.2858    .0226     .0298    .3936
4.8460    1.0000     .0665   .0885     .7507    .4531    −.1074    .2403
6.5015     .0000     .0624   .1069     .5831    .5600    −.1476    .2724
6.5015    1.0000    −.0829   .1152    −.7198    .4719    −.3090    .1432

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
    binladen       age       sex     stereo        se      LLCI     ULCI.

BEGIN DATA.
      .0000    3.1905     .0000     2.6697     .0752    2.5219    2.8174
     1.0000    3.1905     .0000     3.0308     .0920    2.8502    3.2114
      .0000    3.1905    1.0000     2.7677     .0664    2.6374    2.8979
     1.0000    3.1905    1.0000     2.9835     .0801    2.8262    3.1408
      .0000    4.8460     .0000     2.8116     .0591    2.6955    2.9277
     1.0000    4.8460     .0000     3.0233     .0712    2.8835    3.1632
      .0000    4.8460    1.0000     2.9096     .0567    2.7982    3.0209
     1.0000    4.8460    1.0000     2.9761     .0679    2.8427    3.1095
      .0000    6.5015     .0000     2.9536     .0681    2.8198    3.0873
     1.0000    6.5015     .0000     3.0159     .0825    2.8539    3.1779
      .0000    6.5015    1.0000     3.0515     .0730    2.9081    3.1949
     1.0000    6.5015    1.0000     2.9686     .0891    2.7938    3.1435

END DATA.
GRAPH/SCATTERPLOT=
 age    WITH    stereo    BY    binladen /PANEL    ROWVAR=    sex .
*****************************************************************
OUTCOME VARIABLE:
 mcivil

Model Summary
          R      R-sq       MSE          F       df1        df2        p
      .5303     .2812     .7699    85.6765    3.0000   657.0000    .0000

Model
               coeff        se          t         p       LLCI      ULCI
constant       .6201     .1324     4.6842     .0000      .3602     .8801
binladen      −.0109     .0698     −.1564     .8758     −.1480     .1261
stereo         .4954     .0423    11.7166     .0000      .4124     .5785
ideo           .1043     .0165     6.3286     .0000      .0720     .1367

************ DIRECT AND INDIRECT EFFECTS OF X ON Y ****************
Direct effect of X on Y
     Effect        se          t         p       LLCI      ULCI
     −.0109     .0698     −.1564     .8758     −.1480     .1261
```

```
Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 binladen     ->     stereo     ->     mcivil

          age        sex     Effect     BootSE     BootLLCI      BootULCI
       3.1905      .0000      .1789      .0585        .0677         .2971
       3.1905     1.0000      .1069      .0509        .0105         .2094
       4.8460      .0000      .1049      .0459        .0165         .1963
       4.8460     1.0000      .0329      .0438       -.0534         .1199
       6.5015      .0000      .0309      .0557       -.0785         .1414
       6.5015     1.0000     -.0411      .0597       -.1608         .0757

        Indices of partial moderated mediation:
          Index       BootSE      BootLLCI      BootULCI
age      -.0447        .0206       -.0861        -.0056
sex      -.0720        .0630       -.2005         .0496
```

Appendix 2

PROCESS code and output for a first stage moderated moderated mediation model.
Only PROCESS version 3 code out and output is provided here. For version 2, see the supplementary materials available at www.afhayes.com and www.processmacro.org

SPSS: **process y=mcivil/x=binladen/m=stereo/w=age/z=sex/cov=ideo/ plot=1/boot=10000/moments=1/model=11.**
SAS: **%process (data=binladen,y=mcivil,x=binladen,m=stereo,w=age, z=sex,cov=ideo,plot=1,boot=10000,moments=1,model=11);**

```
************* PROCESS Procedure for SPSS Release 3.00 ************
Model :  11
    Y :  mcivil
    X :  binladen
    M :  stereo
    W :  age
    Z :  sex

Covariates:
 ideo

Sample
Size: 661

*****************************************************************
OUTCOME VARIABLE:
 stereo

Model Summary
          R       R-sq        MSE          F        df1         df2         p
      .3789      .1436      .6408    13.6635     8.0000    652.0000     .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.6459      .1974     8.3375      .0000     1.2583     2.0336
binladen     1.1369      .2999     3.7905      .0002      .5480     1.7259
age           .0987      .0344     2.8686      .0043      .0311      .1663
Int_1        -.1859      .0559    -3.3232      .0009     -.2957     -.0760
Sex           .2238      .2514      .8905      .3735     -.2697      .7174
```

```
Int_2        -1.0395     .4013     -2.5902     .0098     -1.8275     -.2515
Int_3         -.0259     .0489      -.5298     .5964      -.1220      .0701
Int_4          .1838     .0782      2.3508     .0190       .0303      .3374
ideo           .1276     .0142      8.9663     .0000       .0996      .1555

Product terms key:
    Int_1  :   binladen x   age
    Int_2  :   binladen x   sex
    Int_3  :   age      x   sex
    Int_4  :   binladen x   age  x  sex

Test(s) of highest order unconditional interaction(s):
      R2-chng        F     df1      df2      p
X*W*Z   .0073   5.5261  1.0000  652.0000  .0190

----------
Focal predict:  binladen (X)
      Mod var:  age      (W)
      Mod var:  sex      (Z)

Test of conditional X*W interaction at value(s) of Z:
        sex     Effect          F       df1         df2        p
      .0000     -.1859    11.0437    1.0000    652.0000    .0009
     1.0000     -.0020      .0014    1.0000    652.0000    .9703

  Conditional effects of the focal predictor at values of moderator(s):

   age      sex     Effect      se        t        p      LLCI     ULCI
3.1905    .0000      .5439   .1410   3.8570    .0001     .2670    .8208
3.1905   1.0000      .0910   .1169    .7781    .4368    -.1386    .3206
4.8460    .0000      .2362   .0928   2.5442    .0112     .0539    .4185
4.8460   1.0000      .0876   .0887    .9883    .3234    -.0865    .2617
6.5015    .0000     -.0715   .1204   -.5937    .5529    -.3079    .1650
6.5015   1.0000      .0843   .1355    .6219    .5342    -.1818    .3503

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   binladen       age       sex     stereo        se      LLCI      ULCI.


BEGIN DATA.
      .0000    3.1905     .0000    2.6452     .0881    2.4721    2.8182
     1.0000    3.1905     .0000    3.1891     .1101    2.9728    3.4053
      .0000    3.1905    1.0000    2.7863     .0749    2.6392    2.9334
     1.0000    3.1905    1.0000    2.8773     .0897    2.7012    3.0534
      .0000    4.8460     .0000    2.8086     .0592    2.6923    2.9249
     1.0000    4.8460     .0000    3.0448     .0715    2.9045    3.1851
      .0000    4.8460    1.0000    2.9069     .0568    2.7954    3.0183
     1.0000    4.8460    1.0000    2.9945     .0680    2.8609    3.1281
      .0000    6.5015     .0000    2.9720     .0758    2.8232    3.1209
     1.0000    6.5015     .0000    2.9005     .0935    2.7170    3.0841
      .0000    6.5015    1.0000    3.0274     .0864    2.8578    3.1970
     1.0000    6.5015    1.0000    3.1117     .1045    2.9065    3.3168
END DATA.
GRAPH/SCATTERPLOT=
  age   WITH   stereo   BY   binladen /PANEL   ROWVAR=  sex .

**************************************************************************
OUTCOME VARIABLE:
  mcivil
```

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5303      .2812      .7699    85.6765     3.0000   657.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .6201      .1324     4.6842      .0000      .3602      .8801
binladen     -.0109      .0698     -.1564      .8758     -.1480      .1261
stereo        .4954      .0423    11.7166      .0000      .4124      .5785
ideo          .1043      .0165     6.3286      .0000      .0720      .1367

************** DIRECT AND INDIRECT EFFECTS OF X ON Y **************
Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0109      .0698     -.1564      .8758     -.1480      .1261

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 binladen    ->    stereo    ->    mcivil

        age        sex     Effect     BootSE   BootLLCI   BootULCI
     3.1905      .0000      .2695      .0730      .1349      .4193
     3.1905     1.0000      .0451      .0542     -.0626      .1505
     4.8460      .0000      .1170      .0461      .0292      .2104
     4.8460     1.0000      .0434      .0440     -.0431      .1317
     6.5015      .0000     -.0354      .0650     -.1660      .0905
     6.5015     1.0000      .0417      .0693     -.0924      .1805

     Index of moderated moderated mediation
     Index     BootSE   BootLLCI   BootULCI
     .0911      .0407      .0136      .1742

     Indices of conditional moderated mediation by W
        sex      Index     BootSE   BootLLCI   BootULCI
      .0000     -.0921      .0311     -.1559     -.0339
     1.0000     -.0010      .0266     -.0528      .0520
```

Indices of conditional moderated mediation by sex at values of age can be generated by swapping the roles of *W* and *Z* in the PROCESS command, as such:

SPSS: **process y=mcivil/x=binladen/m=stereo/w=sex/z=age/cov=ideo/ plot=1/boot=10000/moments=1/model=11.**

SAS: **%process (data=binladen,y=mcivil,x=binladen,m=stereo,w=sex, z=age,cov=ideo,plot=1,boot=10000,moments=1,model=11);**

Appendix 3

PROCESS code and output for the first and second stage dual moderated mediation model. Only PROCESS version 3 code out and output is provided here. For version 2, see the supplementary materials available at www.afhayes.com and www.processmacro.org

SPSS: **process y=mcivil/x=binladen/m=stereo/w=age/z=sex/cov= ideo/plot=1/moments=1/boot=10000/model=21.**

SAS: **%process (data=binladen,y=mcivil,x=binladen,m=stereo,w= age,z=sex,cov=1,plot=1,moments=1,boot=10000,model=21);**

```
************ PROCESS Procedure for SPSS Release 3.00 ****************
Model :  21
    Y :  mcivil
```

```
    X :  binladen
    M :  stereo
    W :  age
    Z :  sex

Covariates:
  ideo

Sample
  Size: 661

*************************************************************
OUTCOME VARIABLE:
  stereo

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3636      .1322      .6453    24.9871     4.0000   656.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.7706      .1444    12.2660      .0000     1.4872     2.0541
binladen      .5413      .1979     2.7347      .0064      .1526      .9299
age           .0815      .0243     3.3544      .0008      .0338      .1292
Int_1        -.0836      .0387    -2.1630      .0309     -.1596     -.0077
Ideo          .1300      .0142     9.1249      .0000      .1020      .1580

Product terms key:
  Int_1    :    binladen x    age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0062     4.6787     1.0000   656.0000      .0309

----------
Focal predict: binladen (X)
      Mod var: age      (W)

Conditional effects of the focal predictor at values of moderator(s):

        age     Effect         se          t          p       LLCI       ULCI
     3.1905      .2744      .0903     3.0388      .0025      .0971      .4517
     4.8460      .1360      .0637     2.1350      .0331      .0109      .2610
     6.5015     -.0025      .0903     -.0278      .9779     -.1798      .1748

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
  binladen        age     stereo         se       LLCI       ULCI.

BEGIN DATA.
      .0000     3.1905     2.7278      .0572     2.6154     2.8402
     1.0000     3.1905     3.0022      .0698     2.8651     3.1393
      .0000     4.8460     2.8626      .0407     2.7827     2.9426
     1.0000     4.8460     2.9986      .0489     2.9026     3.0945
      .0000     6.5015     2.9975      .0572     2.8852     3.1098
     1.0000     6.5015     2.9950      .0699     2.8578     3.1322
END DATA.
GRAPH/SCATTERPLOT=
age       WITH       stereo     BY      binladen  .

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

```
OUTCOME VARIABLE:
  mcivil

Model Summary

          R       R-sq        MSE          F        df1        df2          p
      .5317      .2827      .7706    51.6313     5.0000   655.0000      .0000

Model

              coeff         se          t          p       LLCI       ULCI
constant      .5179      .1803     2.8728      .0042      .1639      .8720
binladen     -.0130      .0699     -.1868      .8519     -.1502      .1241
stereo        .5378      .0586     9.1803      .0000      .4228      .6529
sex           .2049      .2420      .8468      .3974     -.2703      .6801
Int_1        -.0828      .0795    -1.0410      .2983     -.2390      .0734
Ideo          .1041      .0165     6.3089      .0000      .0717      .1365

Product terms key:
  Int_1    :    stereo    x    sex

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*Z      .0012     1.0837     1.0000   655.0000      .2983

----------
Focal predict: stereo (M)
      Mod var: sex    (Z)

Conditional effects of the focal predictor at values of moderator(s):

        sex     Effect         se          t          p       LLCI       ULCI
      .0000      .5378      .0586     9.1803      .0000      .4228      .6529
     1.0000      .4550      .0575     7.9069      .0000      .3420      .5680

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
     stereo        sex        mcivil        se         LLCI        ULCI.

BEGIN DATA.

     2.0589      .0000     2.1781      .0703     2.0400     2.3162
     2.9186      .0000     2.6405      .0494     2.5435     2.7375
     3.7783      .0000     3.1029      .0708     2.9639     3.2418
     2.0589     1.0000     2.2125      .0686     2.0778     2.3473
     2.9186     1.0000     2.6037      .0473     2.5109     2.6965
     3.7783     1.0000     2.9949      .0682     2.8610     3.1289
END DATA.
GRAPH/SCATTERPLOT=
 stereo    WITH    mcivil    BY    sex .

*************** DIRECT AND INDIRECT EFFECTS OF X ON Y ***************
Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0130      .0699     -.1868      .8519     -.1502      .1241

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 binladen    ->    stereo    ->    mcivil

        age        sex     Effect     BootSE   BootLLCI   BootULCI
```

```
3.1905      .0000      .1476      .0497       .0545       .2498
3.1905     1.0000      .1249      .0420       .0464       .2113
4.8460      .0000      .0731      .0346       .0070       .1423
4.8460     1.0000      .0619      .0301       .0059       .1233
6.5015      .0000     -.0013      .0521      -.1056       .0985
6.5015     1.0000     -.0011      .0443      -.0887       .0866

Index of moderated moderated mediation
Index      BootSE      BootLLCI      BootULCI
.0069      .0083        -.0055         .0269

Indices of conditional moderated mediation by W
   sex         Index        BootSE        BootLLCI        BootULCI
 .0000        -.0450         .0226         -.0912          -.0030
1.0000        -.0381         .0187         -.0758          -.0026
```

The following command generates indices of conditional moderated mediation by sex at values of age for this model:

SPSS: **process y=mcivil/x=binladen/m=stereo/w=sex/z=age/cov=ideo/ moments=1/plot=1/boot=10000/bmatrix=1,1,1/wmatrix=0,0,1/ zmatrix=1,0,0.**

SAS: **%process (data=binladen,y=mcivil,x=binladen,m=stereo,w=sex, z=age,moments=1,cov=1,plot=1,boot=10000,bmatrix=1 1 1, wmatrix=0 0 1,zmatrix=1 0 0);**