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Conditional Process Analysis: Concepts, Computation, and Advances in the Modeling of the Contingencies of Mechanisms

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Abstract

Behavioral scientists use mediation analysis to understand the mechanism(s) by which an effect operates and moderation analysis to understand the contingencies or boundary conditions of effects. Yet how effects operate (i.e., the mechanism at work) and their boundary conditions (when they occur) are not necessarily independent, though they are often treated as such. Conditional process analysis is an analytical strategy that integrates mediation and moderation analysis with the goal of examining and testing hypotheses about how mechanisms vary as a function of context or individual differences. In this article, we provide a conceptual primer on conditional process analysis for those not familiar with the integration of moderation and mediation analysis, while also describing some recent advances and innovations for the more experienced conditional process analyst. After overviewing fundamental modeling principles using ordinary least squares regression, we discuss the extension of these fundamentals to models with more than one mediator and more than one moderator. We describe a *differential dominance conditional process model* and overview the concepts of *partial, conditional*, and *moderated moderated mediation*. We also discuss multilevel conditional process analysis and comment on implementation of conditional process analysis in statistical computing software.

Keywords

moderation analysis, mediation analysis, conditional process analysis, multilevel modeling

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Behavioral scientists strive to do more with their research than establish whether an effect of some kind exists. Our theories also yield hypotheses about how those effects come to be and the circumstances under which those effects exist or do not. The former ("how" an effect operates, i.e., the mechanism or process at work) speak to *mediators* of an effect, and the latter ("when" or "for whom" an effect exists) speak to *moderators* of an effect. For example, the literature on a new therapeutic method to treat substance use disorders might show not only that it is more effective than other treatments but also that the greater effectiveness can be attributed to the method reducing rumination about negative life events (a *mediator* variable), which then lessens craving for substances to deal with the uncomfortable emotions resulting from dwelling on past negative experiences. Furthermore, perhaps the new method is more effective among people who have more social support (a *moderator* variable). It might even be less effective than other treatments for people who have no one to rely on for the support needed to break an addiction.

Many researchers would feel satisfied establishing how and when an effect exists. But the best researchers are now going further in their science by examining the *contingencies of processes*. Perhaps this new therapeutic method is more effective with people who receive more social support because the method works better at reducing rumination in the presence of more social support, and this reduction in rumination then helps overcome experiences of craving and substance use. In the absence of strong social network, the new therapy may have no effect on rumination, and so the benefits of reduced rumination are not experienced, and hence substance use is unaffected. In other words, the process by which the therapy affects substance use differs in a systematic way as a function of social support.

Conditional process analysis is used to examine the extent to which the mechanism(s) by which an effect operates depends on or varies across situation, context, stimulus, or individual differences. Although conditional process analysis is a relatively new term, introduced into the literature in 2013 (Hayes & Preacher, 2013; also in the first edition of Hayes, 2018a), the idea of analytically combining moderation and mediation is not new. Some of the seminal articles in mediation analysis discussed their integration (Baron & Kenny, 1986; James & Brett, 1985; Judd & Kenny, 1981). And in the past decade or so, several important articles and a few books have introduced systematic approaches to integrating moderation and mediation analysis (Edwards & Lambert, 2007; Fairchild & MacKinnon, 2009; Hayes, 2018a; Langfred, 2004; MacKinnon, 2008; Muller, Judd, & Yzerbyt, 2005; Preacher, Rucker, & Hayes, 2007; VanderWeele, 2015).

Although conditional process analysis is becoming more common, it remains obscure or unknown to many. Furthermore, the methods literature has been growing to deal with increasingly complex conditional process modeling problems. It is hard for the newcomer to catch up and feel confident in what he or she is doing, and those with more experience may not yet be aware of how it has been extended. So this article is designed to both help the newcomer catch up and inform the more seasoned conditional process analyst about recent advances in the literature.

Before discussing conditional process analysis, we first address its foundations: moderation and mediation analysis. This material, which will be a review for some readers, includes defining an *indirect effect* and a *conditional effect* and how these are quantified as mathematical functions of regression coefficients. This review is a background for understanding the integration of moderation and mediation analysis and some recent innovations, the main topic of this article. We show how an indirect effect, as a quantification or empirical representation of a mediation process, can be specified as a linear function of a moderator and how this function can be used to test whether an indirect effect is moderated. We then discuss one form of an intriguing kind of conditional process model with more than one mediator, a *differential dominance conditional process model*, that allows one mechanism to dominate for certain people or in certain contexts but another to dominate for other types of people or in other contexts. We then address models that have more than one moderator of a mechanism, a topic that has largely been neglected by methodologists until recently, and explain the concepts of *partial moderated mediation, conditional moderated mediation*, and *moderated moderated mediation*. We then shift to advances in mediation analysis in hierarchically structured data and their extension to multilevel conditional process analysis, describing how some of the principles discussed in the first half of the article generalize to multilevel analysis. In two sections, one dedicated to single-level and the other to multilevel analysis, we comment on the implementation of the methods we discuss in statistical software.

Conditional process analysis is a vast topic. Our discussion is limited to the fundamentals of the estimation of effects using linear regression analysis, which is the most common approach to conditional process analysis. Understanding this application of the fundamentals facilitates their use with more complicated analytical procedures and computing platforms. This limitation in our treatment means that we focus on models of outcomes (variables on the left sides of equations) that are continuous in nature and analyzed assuming at least interval-level measurement. Predictor variables (on the right sides of equations) are also assumed to be at least interval-level measures or dichotomous. These variables may be either manipulated experimentally or merely measured. Although causal models ultimately involve processes that evolve over time, we do not address longitudinal models (though two- or three-wave panel designs can be analyzed using methods we do discuss by using earlier measurements as covariates in models of later measurements). And we neglect any discussion of the counterfactual (aka potential outcomes) perspective, a movement that is gaining traction in the behavioral sciences but still remains relatively rare in practice. That means that we assume no interaction between causal agent X and a mediator in the model of the penultimate outcome (our approach and the counterfactual approach are largely identical with this assumption). See VanderWeele (2015) for a discussion of the counterfactual framework.

Before beginning, we make explicit our position on the role of statistics in cause-effect analysis. Causal models, as conditional process models are, cannot be definitively proven using any statistical procedure. But statistical methods can be used to quantify relationships that may be causal in nature. Statistics can inform causal arguments one is making, but statistics cannot be the sole basis of the argument. Cause–effect is established through good research design as well as convincing theoretical argument backed up by statistical evidence. Interpreting a measure of association between variables as causal requires many assumptions, many which are not directly testable, and others that can be satisfied by design decisions but not by mathematical manipulation and computation. For a discussion of the assumptions of causal inference in mediation analysis, see Imai, Keele, and Tingley (2010); Preacher (2015); and VanderWeele (2016).

Our position is different, and more relaxed, than the ones held by those who believe mediation analysis (and, therefore, conditional process analysis) using correlational data without a time component or random assignment is "almost certainly futile" (Maxwell, Cole, & Mitchell, 2011), or that there should be a moratorium on mediation analysis with cross-sectional data. We believe that any mathematical procedure can inform the questions you are asking of your data because the mathematics are not the inference. The inference comes from your brain making sense of the results of a mathematical procedure. In this article, we use causal terms such as *affects* and *influences* rather casually when interpreting *effects* because we understand that you appreciate that causal claims require far more than numerical estimation and statistical inference and that association observed between variables typically has both causal and noncausal interpretations. Certainly, correlation does not imply causation, but sometimes two variables are correlated because they are causally related. Instead of restricting conditional process analysis to certain categories of research designs, we prefer to see it applied more broadly, even in imperfect studies but with causal arguments that are well articulated. We would like more research to see the light of day rather than restrict publication to only definitive studies that satisfy all critics, that have no alternative interpretations other than the one the authors advance, and that eliminate the need for future research. If we published only such beauties—those unicorns feeding from the pot of gold near the base of the rainbow—the evolution of our understanding of human behavior would slow to a crawl.

Mediation and Moderation

Before exploring advances in the modeling of the contingencies of mechanisms, familiarity with the fundamentals of mediation and moderation analysis is necessary, as the principles of these analytical methods must be understood before it is possible to understand their integration into a unified conditional process model. In this section, we overview those principles.

Mediation

Variable X's effect on a second variable Y is said to be mediated by a third variable M if X causally influences M and M in turn causally influences Y. So X influences Y by inducing change in a *mediator variable* M, which then carries X's influence on to Y. For example, Hagtvedt and Patrick (2008) report that by associating a product with art (X), people evaluate the product more positively (Y) because connecting a product with art results in a perception that the product is luxurious (M) and people tend to feel good about luxurious things. So perceptions of luxuriousness functions as a mediator of the effect of art infusion on product evaluation.

A mediation process is represented conceptually in Figure 1, panel A. The arrows represent an effect from the variable sending the arrow on the variable receiving it. These effects can be quantified using various statistical procedures, recognizing the limited role that statistics can play in causal inference discussed above. Assuming that *M* and *Y* are continuous variables, *X* is either dichotomous or continuous, and that the relationships between *X, M*, and *Y* are linear in form, ordinary least squares regression analysis is a widely used framework for mediation analysis, though structural equation modeling (SEM) is also often used. A simple mediation model takes the form of two equations:

$$M_i = i_M + aX_i + e_{M_i}$$

$$Y_i = i_Y + c'X_i + bM_i + e_{Y_i},$$

where *i* denotes case or observation, i_M and i_Y are regression constants, and e_{M_i} and e_{Y_i} are errors in estimation of M_i and Y_i. But throughout the rest of this article, we write regression equations using estimated outcome notation, removing the error term or "residuals" to simplify the expressions a bit. We also eliminate the *i* subscript henceforth, acknowledging that *X, M*, and *Y* are always measured on each case. So, these equations are written instead as

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

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

where $\widehat{M}$ and $\hat{Y}$ refer to estimates of *M* and *Y*.

In Equations 1 and 2, *a* quantifies the effect of *X* on *M*, and *b* quantifies the effect of *M* on *Y* independent of *X*. Coefficient *a* is interpreted as the estimated difference in *M* between two cases that differ by one unit on *X*, and *b* is interpreted as the estimated difference in *Y* between two cases that differ by one unit on *M* but that are equal on *X*. Their product, *ab*, is the *indirect effect* of *X* on *Y* through *M* and estimates the difference in *Y* between two cases that differ by one unit on *X* through the joint effect of *X* on *M*, which, in turn, influences *Y*. Assuming that *a* and *b* are estimating causal effects, an inference about the product of *a* and *b* provides a formal test of mediation of the effect of *X* on *Y* through *M*. Because the sampling distribution of *ab* is irregular in form, asymmetric confidence interval approaches have become popular for conducting statistical inference about mediation, such as the bootstrap confidence interval (for a discussion of the mechanics, see Hayes, 2018a; Shrout & Bolger, 2002), the Monte Carlo confidence interval (MCCI; Preacher & Selig, 2012), the distribution of the product approach (MacKinnon, Fritz, Williams, & Lockwood, 2007), and Bayesian

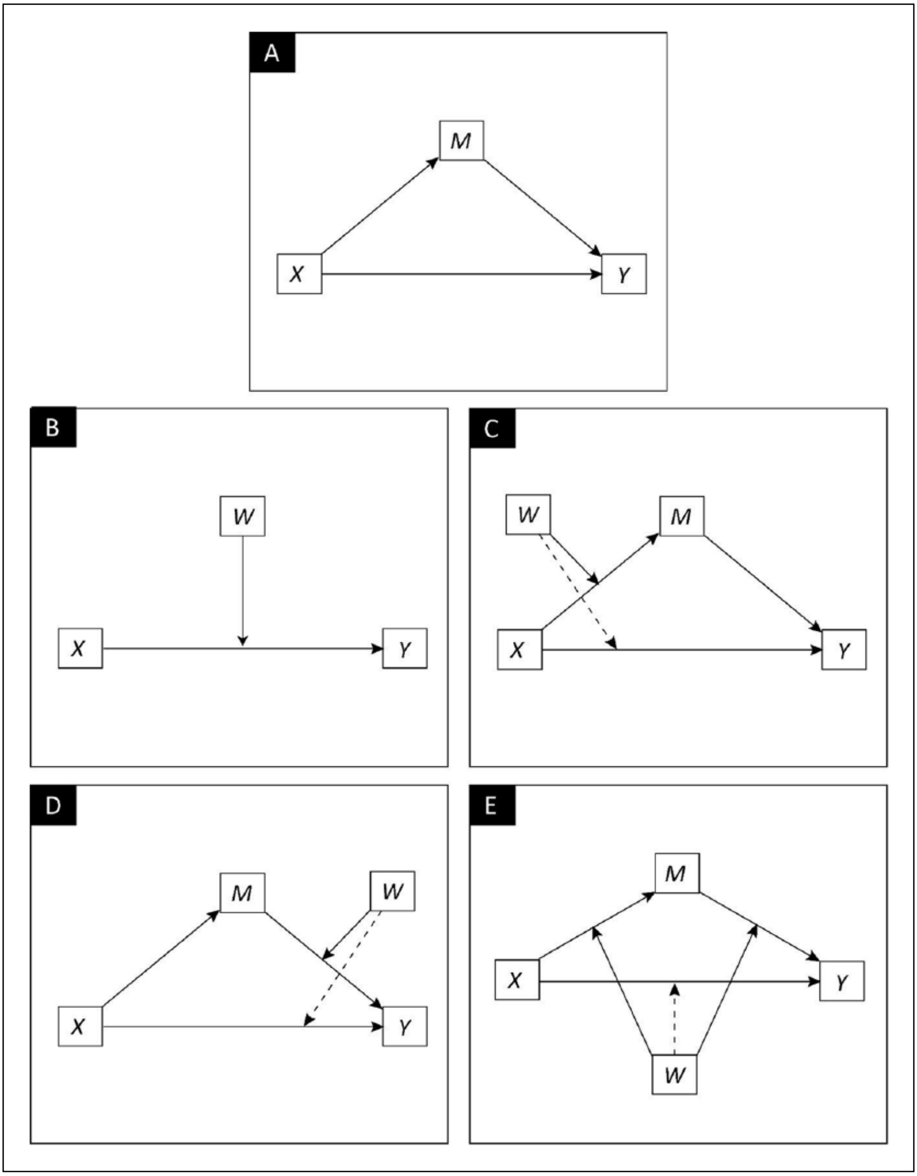


Figure 1. Conceptual representations of mediation (panel A), moderation (panel B), and the first (panel C), second (panel D), and first- and second-stage (panel E) conditional process models.

methods (Yuan & MacKinnon, 2009). The Sobel test (Sobel, 1982), though still used by some, should be avoided because it inappropriately assumes that the sampling distribution of *ab* is normal. We also recommend avoiding the *test of joint significance*, which requires statistically significant a and b to support a mediation claim. The indirect effect is ab, not a and b themselves. Statistically significant estimates of a and b are not a requirement of mediation. Gone are the days of the "criteria to establish mediation" that Baron and Kenny (1986) ushered in.

So ab captures the part of effect of X on Y that operates indirectly through M. The remaining component of X's effect on Y is the *direct effect* of X, quantified by c' in Equation 2. However, it is not typically of much interest in mediation analysis. It quantifies the part of the relationship between X and Y not attributable to the mechanism through M. It is everything about the relationship between X and Y *except* the mediation process that is a part of the model. For this reason, we deemphasize the direct effect of X in this article.

When OLS regression is used to estimate the regression coefficients in Equations 1 and 2, the sum of the direct (c') and the indirect effects (ab) of X is equal to c in

$$\hat{Y} = i_Y + cX.$$

This regression weight, c, is the *total effect* of X and is interpreted as the estimated difference in Y between two cases that differ by one unit on X. But if $c = c' + ab$, it follows that $ab = c - c'$. Thus, one interpretation of the indirect effect is the change in the effect of X on Y when M is allowed to freely vary across cases compared with when it is fixed at some value (any value, since nothing in this model allows the effect of X on Y to vary with M).

Moderation

A variable's effect on another is moderated if its size depends on a third variable—a *moderator*. If the art infusion effect described earlier is larger among people with lower income, then income moderates the effect of art infusion on product evaluation. Moderation, depicted conceptually in Figure 1, panel B, can take many forms, but linear moderation is by far the most commonly assumed form. If interest is in whether X's effect on Y is linearly moderated by W,

$$\hat{Y} = i_Y + b_1 X + b_2 W + b_3 XW \tag{3}$$

is typically estimated, where XW is the product of X and W. If W moderates X's effect on Y, it is said that X and W *interact* in their influence on Y. Equation 3 can be written in an equivalent form as

$$\hat{Y} = i_Y + (b_1 + b_3 W)X + b_2 W, \tag{4}$$

which shows that X's effect on Y is a linear function of W. The weight for X in Equation 4, $b_1 + b_3 W$ is the *conditional effect* of X on Y. It is conditional because its value depends on W. It is a linear model of moderation of the effect of X because the conditional effect of X on Y changes by a constant amount b_3 as W changes by a constant amount.

The conditional effect of X estimates the difference in Y between two cases that differ by one unit on X but with a common value of W. Because W is in the function defining the conditional effect of X, X's effect will depend on that common value of W unless b_3 is exactly zero. When b_3 is zero, then X's effect does not vary across values of W, at least not in a linear fashion. Any value of b_3 different from zero means that X's effect depends on W. Thus, an inference about b_3 is used to test whether W linearly moderates X's effect on Y.[1]

Conditional Process Analysis: Indirect Effects as Functions of a Moderator

X's effect on Y through a mediator M is represented statistically as a product of its constituent causal effects (the effect of X on M and the effect of M on Y). But an effect can be moderated, with linear moderation being a popularly assumed form. Because a mediation process is a conjunction of effects and effects can be moderated, it follows that mediation can be moderated. Moderation of mediation manifests itself statistically in the form of an indirect effect that depends on a moderator, meaning that it is a *function* of a moderator. That function may be linear or nonlinear, depending on the form of the model. It can also be a function of more than one moderator. In this section, we provide examples of three conditional process models that allow an indirect effect to be moderated, discuss the fundamentals of conditional process analysis using regression analysis, show how an indirect effect in a conditional process model can be represented as function of a moderator, and discuss how to test whether an indirect effect is moderated.

The two most popular forms of conditional process models are the *first-stage* conditional process model, depicted in Figure 1, panel C, and the *second-stage* conditional process model, depicted in Figure 1, panel D. In the first-stage model, the moderator W operates on the first stage of the mediation process, with W moderating the effect of X on M but M's effect on Y is fixed to be independent of W and any other variable in the model. In the second-stage model, the moderator W operates only on the second stage of the mediation process, with M's effect on Y specified to vary across W but X's effect on M fixed to be independent of W.

Examples of both of these models are in abundance in the literature (see, e.g., Deng, Coyle-Shaprio, & Yan, 2018; Shapero & Steinberg, 2013; Torres & Taknint, 2015). For instance, Witkiewitz and Bowen (2010) proposed that depression (X) can result in substance use because a negative psychological state precipitates an urge for relief from that state in the form of craving for substances such as alcohol and drugs (M), which heightens the likelihood of substance use (Y). However, they proposed that this link could be broken through a therapeutic method founded on principles of mindfulness because mindfulness training leads people to see that their negative states are transient and need not be relieved through action but merely by waiting for the feeling to subside. They found that in substance abusers randomly assigned to receive either mindfulness training or therapy as usual (W), the relationship between depression and craving (the effect of X on M) was weaker among those who received mindfulness training, and so the indirect effect of depression on substance use through craving was moderated by therapeutic method.

In Witkiewitz and Bowen (2010), the moderator of the indirect effect was dichotomous. But a moderator can be a continuous dimension, as in Cole, Walker, and Bruch (2008) in their second-stage conditional process model examining the effect of dysfunctional team behavior on performance. They found that work teams that engage in relatively more dysfunctional behavior (*X*) produce a more negative emotional work climate (*M*) where team members are feeling annoyed and irritated with one another, and the resulting conflict reduces performance of the team (*Y*). However, this mechanism was more pronounced among teams whose members were more emotionally expressive (*W*). So the effect of negative emotions (*M*) on performance (*Y*) is moderated by the emotional expressivity of the team.

Both the first and the second stage of a mechanism can be moderated by a common variable. The result is a *first- and second-stage* conditional process model, depicted in Figure 1, panel E. For example, Papadaki and Giovazolias (2015) proposed that a child's depression (*M*) functions as a mediator of the effect of maternal rejection (*X*) on the child's tendency to bully others (*Y*) but that the effects of maternal rejection on depression and depression on bullying would be less pronounced the more acceptance the child received from the father (*W*). Hence, they hypothesized that the strength of this mechanism would be dependent on paternal acceptance. See S. Kim and Labroo (2011) and Parade, Leerkes, and Blankson (2010) for additional examples of the first- and second-stage conditional process model.

We next discuss the specification of these conditional process models using a set of linear regression equations. Comfort with the fundamentals described below is important to properly conduct a conditional process analysis and to understand the advances in conditional process analysis that we describe later.

The first-stage conditional process model can be specified using regression equations for *M* and *Y*, with the equations for *M* and *Y* allowing the effect of *X* to be linearly dependent on *W* but the effect of *M* on *Y* to be a fixed, constant value (as in Figure 1, panel C):

$$\begin{aligned}\widehat{M} &= i_M + a_1X + a_2W + a_3XW \\ &= i_M + (a_1 + a_3W)X + a_2W\end{aligned} \tag{5}$$

$$\hat{Y} = i_Y + c'X + bM. \tag{6}$$

If desired, Equation 6 can be modified by including *W* and *XW* as predictors in order to allow the direct effect of *X* to be linear moderated by *W* (denoted with the dashed arrows in Figure 1, panel C). Doing so does not modify the discussion that follows.

The indirect effect of *X* on *Y* through *M* is the product of the effect of *X* on *M* in Equation 5 and the effect of *M* on *Y* in Equation 6:

$$(a_1 + a_3W)b = a_1b + a_3bW, \tag{7}$$

which is a linear function of W. The weight for W in this function, a_3b, is the *index of moderated mediation* for this model (Hayes, 2015). If there is no relationship between moderator W and the size of the indirect effect, then the expectation is that $a_3b = 0$. So, an inference about the size of a_3b is a test of moderation of the indirect effect by W (Hayes, 2015; also see Morgan-Lopez & MacKinnon, 2006). Because the index is a product of regression coefficients, a bootstrap confidence interval can be used for inference without assuming anything about the shape of its sampling distribution. In the special case where W is a dichotomous variable represented in the data with values that differ by one unit (e.g., $W = 0$ and $W = 1$), the index of moderated mediation is the difference between the indirect effect of X on Y in the two groups.[2]

The second-stage conditional process model fixes the effect of X on M to be constant but allows the effect of M on Y to be moderated by W (Figure 1, panel D). Assuming linear moderation of the effect of M on Y, this model can be specified using

$$\widehat{M} = i_M + aX \tag{8}$$

$$\begin{aligned}\hat{Y} &= i_Y + c'X + b_1M + b_2W + b_3MW \\ &= i_Y + c'X + (b_1 + b_3W)M + b_2W,\end{aligned} \tag{9}$$

with XW added to the right side of Equation 9 if desired to allow the direct effect of X to be moderated by W (the dashed allows in Figure 1, panel D). In this model, the indirect effect of X is the product of the effect of X on M from Equation 8 and the effect of M on Y in Equation 9:

$$a\left(b_1 + b_3W\right) = ab_1 + ab_3W, \tag{10}$$

which is a linear function of W. The index of moderated mediation in this model is ab_3. As in the first-stage model, an inferential test that this index is statistically different from zero provides a formal test of moderation of the indirect effect of X by W. The index of moderated mediation is equivalent to the difference between indirect effects of the two groups when W is dichotomous and coded by two values that differ by one unit.

The first- and second-stage conditional process model (Figure 1, panel E) is specified like any mediation model but includes products XW and MW in the models of M and Y, respectively, as in

$$\begin{aligned}\widehat{M} &= i_M + a_1X + a_2W + a_3XW \\ &= i_M + (a_1 + a_3W)X + a_2W\end{aligned} \tag{11}$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2W + b_3MW \\ = i_Y + c'X + (b_1 + b_3W)M + b_2W. \quad (12)$$

XW can be added to Equation 12 to allow the direct effect of X to be moderated by W (the dashed arrows in Figure 1, panel E).

The indirect effect of X is the product of the effect of X on M in Equation 11 and the effect of M on Y in Equation 12:

$$(a_1 + a_3W)(b_1 + b_3W) = a_1b_1 + (a_1b_3 + a_3b_1)W + a_3b_3W^2. \quad (13)$$

Observe that Equation 13 is a *nonlinear* function of W. When W is a continuum, there is no index of moderated mediation for the first- and second-stage conditional process model, and so a test of moderation of the indirect effect of X by W must be conducted differently than in models with only a single path defining an indirect effect specified as moderated. Hayes (2015, 2018a) recommends choosing two values of the moderator W, w_1 and w_2, and constructing a bootstrap confidence interval for the difference between the conditional indirect effects of X at those two values. If the confidence interval does not include zero, this supports moderation of the indirect effect by W. But a confidence interval that includes zero does not disconfirm moderation of mediation, because it is possible that alternative choices for w_1 and w_2 would produce a bootstrap confidence interval for the difference that does not include zero. So, this approach can be used to confirm but not disconfirm moderation of mediation.[3]

The mathematics presented above illustrate how a conditional process model yields an indirect effect of X on Y that is a function of a moderator. With evidence of moderation of mediation, this moderation can be "probed" by estimating the conditional indirect effect of X at various values of moderator W (using Equations 7, 10, or 13) and conducting an inferential test for the conditional indirect effect at those values, with a bootstrap confidence interval being the typical inferential approach. The pattern of results can yield claims about where in the distribution of W that X's effect on Y is mediated by M and where it is not. When W is dichotomous, the two values of W chosen to code the two groups can be used in place of W in Equations 7, 10, or 13. If W is a continuum, values of W are typically chosen, often arbitrarily, that operationalize "relative low," "relatively moderate," and "relatively high" on the moderator.

Conditional Process Analysis With More Than One Mediator

There are many published treatments of the integration of moderation and mediation analysis, but they primarily have focused on the simplest case of a single mediator and a single moderator. This has left researchers to figure out how to approach conditional process analysis for models that involve more than one mediator or moderator. Here, we discuss the application of the principles described earlier to more complex models with multiple mediators but only a single moderator. In the next section, we address models with more than one moderator.

A variable X can pass its effect to Y through more than one mediator simultaneously. Multiple mediator models include multiple mechanisms linking X to Y and allow for tests that compare the relative size or strength of those mechanisms (see Preacher & Hayes, 2008; MacKinnon, 2008). Mediators can be arranged in parallel form (as in Figure 2, panel A; e.g., Bizumic, Kenny, & Iyer, Tanuwira, & Huxley, 2017; Jones, Willness, & Madey, 2014), or in serial form (as in Figure 2, panel B; e.g., Druckman & Wagner, 2019; Harinck & Druckman, 2017). Parallel and serial mediation can also be blended in a single model, as in Figure 2, panel C (for examples, see, e.g., Gratz, Bardeen, & Levy et al., 2015; Robertson & Barling, 2013). Any of the paths in a multiple mediator model could be moderated, resulting in an indirect effect that is a function of that moderator.

In a multiple mediator model, there is more than one indirect effect of X, each called a *specific indirect effect* and quantified as a product of pathways linking X to Y. For example, in a parallel multiple mediator model as in Figure 2, panel A, there is an indirect effect of X on Y through each mediator. The indirect effect through mediator j is defined as the product of the effect of X on M_j and the effect of M_j on Y. In a serial multiple mediator model with two mediators, as in Figure 2, panel B, there are two specific indirect effects that pass through a single mediator, calculated by multiplying its constituent effects as in the parallel model, plus a serial indirect effect constructed as the product of the effects of X on M_1, M_2 on M_2, and M_2 on Y. In such models, the two (or more in a serial or blended multiple mediation model) effects that are multiplied together to produce an indirect effect could be specified as moderated by the same moderator, different moderators, or no moderator at all. This produces many possible conditional process models that one could construct in a model with only two mediators. The addition of more mediators further increases the possibilities.

Some conditional process models with one moderator but two or three mediators are depicted in Figure 2, panels D, E, and F, but these represent only a small fraction of the possibilities. For instance, Barling and Weatherhead (2016) examined school quality (M_1) and personal mastery (M_2, the belief that obstacles can be overcome) as parallel mediators of the effect of early exposure to poverty (X) on leader emergence (Y) among adolescents and young adults, with the effect of personal mastery on leadership emergence as well as the direct effect of school quality on leadership emergence differing between males and females (W) (as in Figure 2, panel D). And Mehta, Demmers, van Dolen, & Weinberg (2017) tested a model like in Figure 2, panel E, that includes both serial mediation and moderation. They found that a public service announcement (about using sunscreen) printed in red as opposed to white (X) resulted in greater noncompliance (Y) because red elicited more arousal (M_1), with arousal prompting greater reactance (M_2) among people higher in sensation seeking (W) than among people lower in sensation seeking, and more reactance was associated with greater noncompliance. Some additional examples of conditional process models with

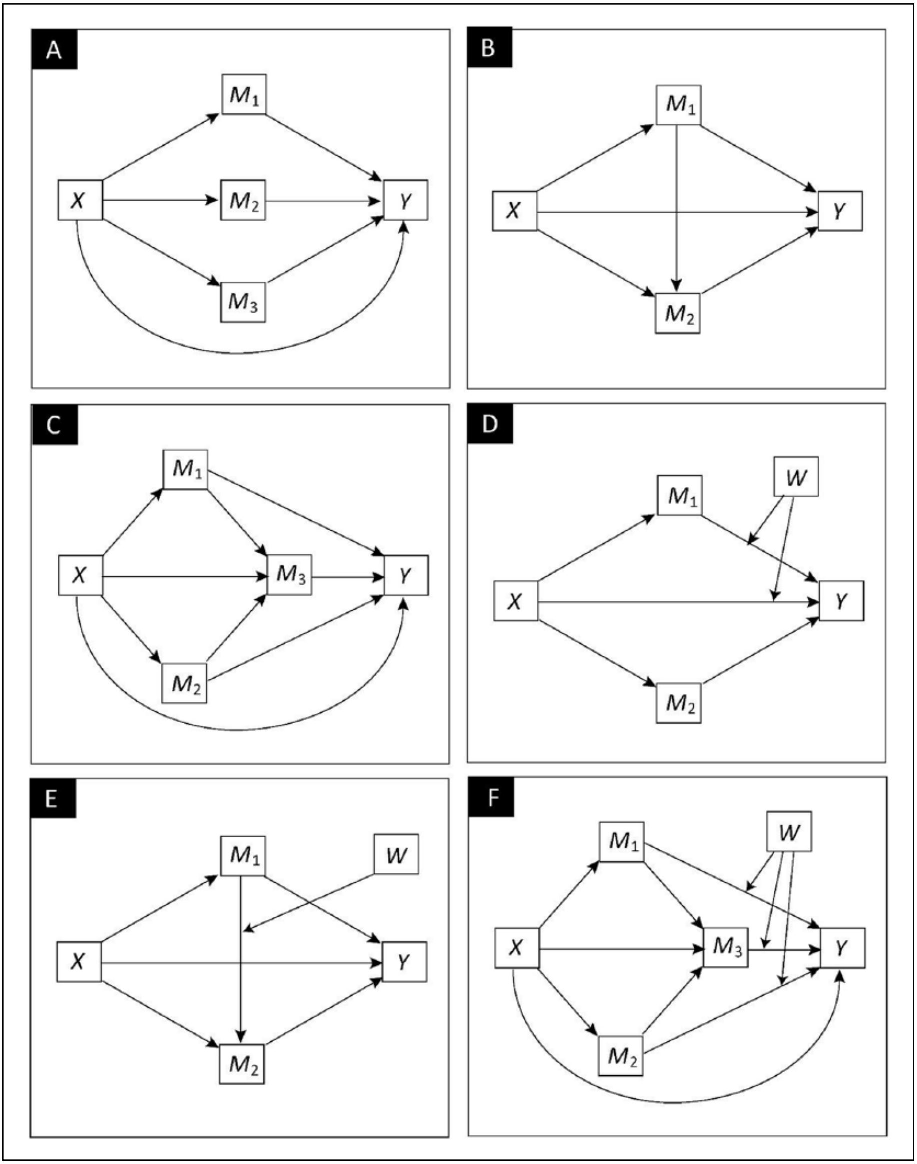


Figure 2. Parallel (panel A), serial (panel B), and blended (panel C) multiple mediator models and some conditional process models with more than one mediator (panels D-F).

a single moderator but more than one mediator include Calabrese et al. (2018), Deery, Walsh, Zatzick, and Hayes (2017), and Dubois, Rucker, and Galinsky (2016).

The specification of a conditional process model with multiple mediators proceeds as it does for simpler models, although with more than one mediator there are additional equations. Consider two mediators operating in parallel, with each of the first-stage effects of X on a mediator specified as moderated by W but each mediator's effect on Y specified as independent of W, as in Figure 3. Assuming linear effects and linear moderation, the three equations below estimate the effects in this model:

$$\begin{aligned}\hat{M}_1 &= i_{M_1} + a_{11}X + a_{12}W + a_{13}XW \\ &= i_{M_1} + (a_{11} + a_{13}W)X + a_{12}W\end{aligned} \tag{14}$$

$$\begin{aligned}\hat{M}_2 &= i_{M_2} + a_{21}X + a_{22}W + a_{23}XW \\ &= i_{M_2} + (a_{21} + a_{23}W)X + a_{22}W\end{aligned} \tag{15}$$

$$\hat{Y} = i_Y + c_1' X + b_1 M_1 + b_2 M_2. \tag{16}$$

The indirect effect of X on Y through M_1 is the product of the conditional effect of X on M_1 in Equation 14 and the unconditional effect of M_1 on Y from Equation 16:

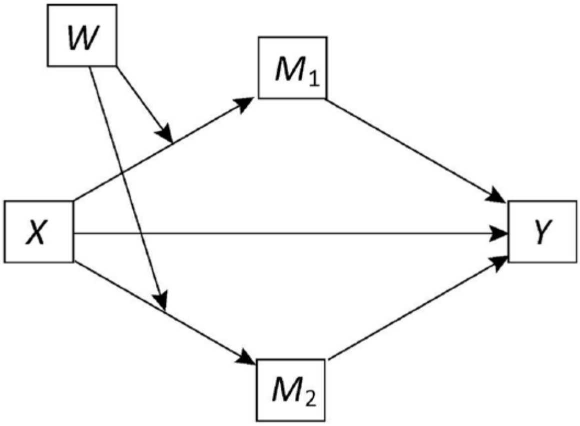
$$(a_{11} + a_{13}W)b_1 = a_{11}b_1 + a_{13}b_1W. \tag{17}$$

The index of moderated mediation of the specific indirect effect of X through M_1 by W is $a_{13}b_1$, the weight for W in Equation 17. Likewise, the indirect effect of X on Y through M_2 is the product of the conditional effect of X on M_2 from Equation 15 and the unconditional effect of M_2 on Y from Equation 16:

$$(a_{21} + a_{23}W)b_2 = a_{21}b_2 + a_{23}b_2W . \tag{18}$$

The index of moderated mediation of the specific indirect effect through M_2 by W is $a_{23}b_2$, the weight for W in Equation 18. Inference about these two indices would support or disconfirm whether the strength of the mechanism through M_1 and/or M_2 depends on W. The conditional indirect effects of X on Y are calculated plugging in the value of W into Equations 17 and 18 and then conducting an inference about these conditional indirect effects. Inference for both the index of moderated mediation and the conditional indirect effects is conducted most easily through the construction of bootstrap confidence intervals.

Such a model, which we call a *differential dominance conditional process model*, allows the mechanism through M_1 to be dominant for a subset of people defined by one value of W but the mechanism through M_2 to be dominant for a subset defined by a different value of W. W need not be dichotomous; the positions on W could be two values on a continuous dimension that operationalize "high" versus "low" on that dimension. Such a pattern of differential dominance was reported by Chen, Wen, and Hu (2017). They examined access to job-related resources and subjective workload as mediators of the effect of job mentoring on work-family conflict. They found that



$$\widehat{M}_1 = i_{M_1} + a_{11}X + a_{12}W + a_{13}XW$$

$$\widehat{M}_2 = i_{M_2} + a_{21}X + a_{22}W + a_{23}XW$$

$$\hat{Y} = i_Y + c_1'X + b_1M_1 + b_2M_2$$

	Conditional indirect effect of X on Y through	
	M_1	M_2
	$(a_{11} + a_{13}W)b_1$	$(a_{21} + a_{23}W)b_2$
"Type A" (W= 0)	**(0.40 – 0.40 × 0) 0.50 = 0.20**	(0.00 + 0.60 × 0) 0.30 = 0.00
"Type B" (W= 1)	(0.40 – 0.40 × 1) 0.50 = 0.00	**(0.00 + 0.60 × 1) 0.30 = 0.18**

Figure 3. Conditional indirect effects from a first-stage differential dominance conditional process model specified by Equations 14 to 16, when $a_{11} = 0.40$, $a_{13} = -0.40$, $a_{21} = 0.00$, $a_{23} = 0.60$, $b_1 = 0.50$, and $b_2 = 0.30$.

among employees of a machine manufacturing facility whose identity revolved more around work than family, mentoring was indirectly related to work-family conflict through access to job-related resources (more mentoring increased access to resources, which was associated with reduced work-family conflict) but not through subjective workload. However, the opposite pattern was found among employees who were more family focused in their identity. Among such employees, mentoring was indirectly related to work-family conflict through subjective workload (more mentoring increased subjective workload, which was related to more work-family conflict) but not through access to job-related resources. Some other examples of the conditional differential dominance of one mechanism over another are found in Brylka, Mähönen, Schellhaas, and Jasinskaja-Lahti (2015) and Phillips, Chamberland, Hekler, Abrams, and Eisenberg (2016).

To illustrate the mathematics of differential dominance, suppose W is a dichotomous variable coded 0 for people of "Type A" and 1 for people of "Type B." Imagine that on estimation of the regression coefficients in Equations 14 to 16, $a_{11} = 0.40$, $a_{13} = -0.40$, $a_{21} = 0.00$, $a_{23} = 0.60$, $b_1 = 0.50$, and $b_2 = 0.30$. The application of Equations 14 to 16 (see Figure 3) using these numbers with W set to 0 reveals that among Type A's the indirect effect of X on Y through M_1 is 0.20 but through M_2 the indirect effect is 0. So, X affects Y through M_1 but not through M_2 for people of Type A. However, among Type B people, the indirect effect of X on Y through M_1 is 0 but through M_2 it is 0.18. So among Type B's, X affects Y through M_2 but not through M_1.

Conditional Process Analysis With Multiple Moderators

Like an effect can operate through multiple mechanisms simultaneously, a mechanism can be moderated by more than one variable. A variety of combinations of moderation and mediation are possible when more than one moderator is used. Some examples can be found in Figure 4, though these are only a subset of the many possible varieties. With models such as these, Hayes (2018b) discusses how questions such as the following can be addressed: Does the mechanism by which X influences Y differ as a function of moderator W independent of the moderation of that mechanism by moderator Z? And does the extent to which W moderates the mechanism by which X influences Y differ between people, circumstance, or stimuli (Z)?

The index of moderated mediation quantifies the relationship between a moderator W and the size of an indirect effect. But this index can be calculated only when a single moderator is specified as moderating one and only one of the paths that define an indirect effect. With more than a single moderator of one or more paths defining an indirect effect, there are different indices that one can calculate that quantify the relationship between a moderator and an indirect effect and that are sensitive to the questions asked above. Hayes (2018b) recently introduced the concepts and corresponding indices of *partial moderated mediation, conditional moderated mediation*, and *moderated moderated mediation*.

If two moderators are specified as moderating a single but common path defining an indirect effect, as in Figure 4, panel A, then the relationship between one of the moderators and the indirect effect can exist independent of or "controlling for" the second moderator. This is *partial moderated mediation* (Hayes, 2018b). Orth, Cornwell, Ohlhoff, and Naber (2017) provide an illustration, whereby a brand advertised with a human face (X) was liked more (Y) than the same brand when advertised without a face, with processing fluency (M) serving as the mechanism by which this effect operated. However,

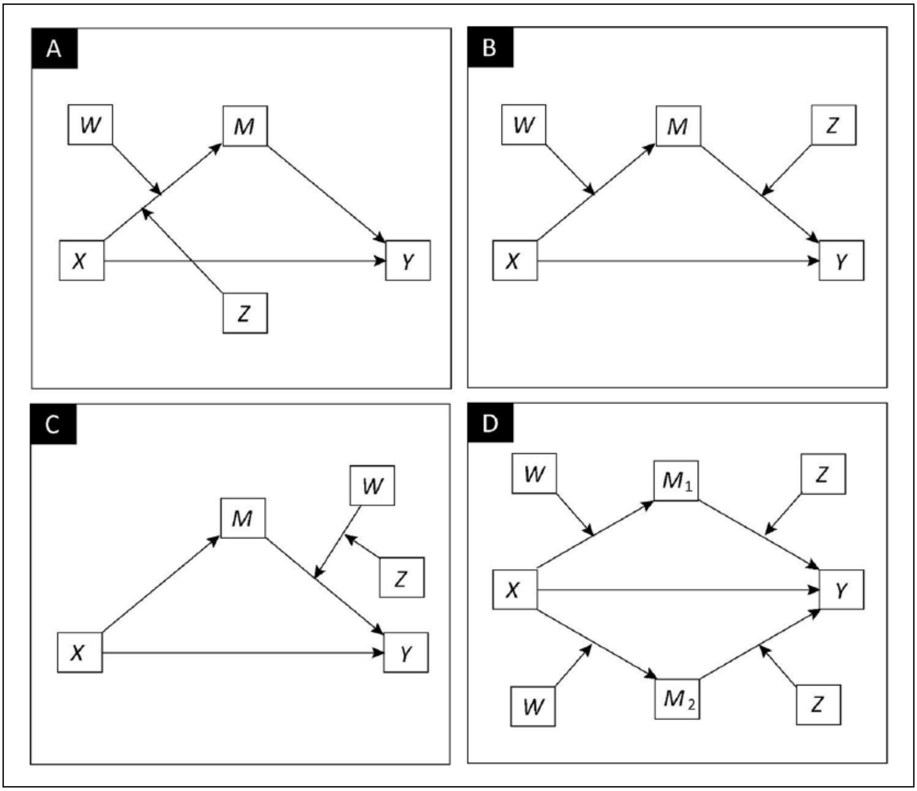


Figure 4. Some conditional process models with two moderators.

both loneliness (W) and the tendency to anthropomorphize (Z) partially moderated this mediation, as the presence of a face resulted in more fluent processing among those scoring higher on a measure of loneliness (independent of anthropomorphizing) or anthropomorphizing tendencies (independent of loneliness). For some other examples of models of this variety, see Goodboy, Bolkan, and Baker (2018) and M. Kim (2018).

Such a model is specified using regression analysis as follows:

$$\begin{aligned}\widehat{M} &= i_M + a_1X + a_2W + a_3Z + a_4XW + a_5XZ \\ &= i_M + (a_1 + a_4W + a_5Z)X + a_2W + a_3Z\end{aligned} \tag{19}$$

$$\hat{Y} = i_Y + c'X + bM\cdot \tag{20}$$

The indirect effect of X on Y through M is the product of the conditional effect of X on M from Equation 19 and the unconditional effect of M on Y from Equation 20:

$$\left(a_1 + a_4W + a_5Z\right)b = a_1b + a_4bW + a_5bZ. \tag{21}$$

In Equation 21, a_4b is *the index of partial moderated mediation* of the indirect effect of X on Y though M by W and a_5b is the index of partial moderated mediation of the same indirect effect by Z. These quantify the relationship between W and the indirect effect of X when Z is held constant and the relationship between Z and the indirect effect of X when W is held constant, respectively. As these are products of regression coefficients, a bootstrap confidence interval is a sensible approach to infer whether W's moderation of a mechanism operates independent of Z's possible moderation of that same mechanism (and vice versa).

In this example, the indirect effect of X on Y through M is an additive function of W and Z (see Equation 21). But if the two moderators are split across different paths that define an indirect effect, then the indirect effect of X on Y through M becomes a more complex function of the two moderators. Figure 4, panel B, displays such a scenario. For instance, A. Li, Shaffer, and Bagger (2015) found that among employees of a caregiving agency, greater caregiving demands (X) were associated with lower psychological well-being (Y) as a result of the work–family conflict (M) that greater demands produces. However, this mechanism was in operation only among caregivers experiencing high family strain (W, as family strain moderated the effect of caregiver demands on work–family conflict) and low supervisor support (Z, as supervisor support moderated the effect of work-family conflict on psychological well-being). See Song, Huang, and Li (2017) and Van Esch and Mente (2018) for additional examples of such a model in the substantive literature.

This model is specified with the equations

$$\begin{aligned} \widehat{M} &= i_M + a_1X + a_2W + a_3XW \\ &= i_M + (a_1 + a_3W)X + a_2W \end{aligned} \tag{22}$$

$$\begin{aligned} \hat{Y} &= i_Y + c'X + b_1M + b_2Z + b_3MZ \\ &= i_Y + c'X + (b_1 + b_3Z)M + b_2Z. \end{aligned} \tag{23}$$

The indirect effect of X on Y through M is the product of the conditional effect of X on M in Equation 22 and the conditional effect of M on Y in Equation 23:

$$\left(a_1 + a_3W\right)\left(b_1 + b_3Z\right) = a_1b_1 + a_3b_1W + a_1b_3Z + a_3b_3WZ \tag{24}$$

(Preacher et al., 2007), and so the indirect effect of X is a function of W, Z, and their product. Two alternative representation of Equation 24 are

$$a_1b_1 + (a_3b_1 + a_3b_3Z)W + a_1b_3Z \tag{25}$$

and

$$a_1b_1 + (a_1b_3 + a_3b_3W)Z + a_3b_1W. \tag{26}$$

As Equations 25 and 26 quantify the indirect effect of X, you can see that the extent to which W moderates the indirect effect of X is a function of Z and the extent to which Z moderates the indirect effect of X is a function of W. This is *moderated moderated mediation* (Hayes, 2018b). The magnitude of moderation of moderated mediation is carried in a_3b_3, the *index of moderated moderated mediation*. An inference about the index of moderated moderated mediation (with a bootstrap confidence interval) is an inference about whether the dependency between moderator W and the strength of the mechanism by which X influences Y differs as a function of Z. Conversely, it allows for a test of dependency between Z and how the size of the indirect effect of X on Y differs as a function of W.

With affirmative evidence of moderated moderated mediation, a natural next step is to estimate the moderation by W of the indirect effect of X on Y at a particular value of Z. This is *conditional moderated mediation* as defined by Hayes (2018b). In Equation 25, the relationship between Z and the extent to which the indirect effect of X on Y depends on W is $a_3b_1 + a_3b_3Z$. When a value of Z is plugged into this function, the result is the *index of conditional moderated mediation* at that value of Z. A test that this index is different from zero serves as a test of moderated mediation of the effect of X on Y through M by W at that value of Z. Using the same logic, from Equation 26, the relationship between W and the extent of the moderation of X's indirect effect on Y by Z is $a_1b_3 + a_3b_3W$. This is the index of conditional moderated mediation by Z at a chosen value of W. Inference about this index serves as a test of moderated mediation of X's effect on Y through M by Z, conditioned on that value of W.

Another interesting combination of moderation and mediation occurs when a variable Z is specified as moderating the *moderation by W* of only one of the paths of an indirect effect, as in Figure 4, panel C. Either the first stage (not depicted in panel C) or the second stage (as depicted) of the mediation process in a model of this sort includes a three-way interaction between X or M and the two moderators W and Z. For example, Krieger and Sarge (2013) examined perceived response efficacy (M) measured after exposure to a cancer screening message as a mediator of the effect of a mother's self-efficacy in encouraging her daughter to talk to her doctor (X) about human papillomavirus (HPV) with the intention to encourage the daughter to get vaccinated against HPV (Y). Their model allowed the effect of perceived response efficacy (i.e., how effective the mother felt talking to the daughter was likely to be) on vaccination communication intentions to depend on the mother's belief about how susceptible her daughter is to getting HPV (W), with the extent of that moderation specified to itself depend on the mother's perceptions of the severity of the consequences of getting HPV (Z). The indirect effect of self-efficacy on intentions through response efficacy was generally positive, but it increased in size with increasing susceptibility among mothers low in perceived severity and decreased with increasing susceptibility among mothers high in perceived severity. Other examples of moderated

moderated mediation models of this form can be found in Freis, Brown, Carroll, and Arkin (2015) and Gilal, Zhang, Gilal, and Gilal (2018).

Consider this model in Figure 4, panel C, which can be estimated using

$$\widehat{M} = i_M + aX \tag{27}$$

$$\begin{aligned}\hat{Y} &= i_Y + c'X + b_1M + b_2W + b_3Z + b_4MW + b_5MZ + b_6WZ + b_7XWZ \\ &= i_Y + c'X + (b_1 + b_4W + b_5Z + b_7WZ)X + b_2W + b_3Z + b_6WZ.\end{aligned} \tag{28}$$

Although this model is functionally different from the example just presented and defined in Equations 22 and 23, the functional form of the indirect effect of *X* on *Y* through *M* is similar. That indirect effect is the product of the unconditional effect of *X* on *M* from Equation 27 and the conditional effect of *M* on *Y* from Equation 28:

$$a(b_1 + b_4W + b_5Z + b_7WZ) = ab_1 + ab_4W + a_5bZ + a_7bWZ,$$

and so the indirect effect of *X* is a function of *W, Z*, and their product, as in the prior example. This is a model that also allows for moderation of moderated mediation and the estimation of moderated mediation conditional on a value of a second moderator. A similar algebra like in the prior example shows that the extent to which *W* moderates the indirect effect of *X* is a function of *Z*—$ab_4 + ab_7Z$—and the extent to which *Z* moderates the indirect effect of *X* is a function of *W*—$ab_5 + ab_7W$. These are the indices of conditional moderated mediation for this model. Each of these contain a_7b, the index of moderated moderated mediation, which quantifies how much the moderation of the indirect effect of *X* on *Y* through *M* by one moderator differs as a function of the second moderator.

So far we have considered conditional process models with a single mediator and moderator, more than one mediator and a single moderator, or multiple moderators and a single mediator. More complex models have more than one mediator and more than one moderator. Figure 4, panel D, represents only one of the multitude of possibilities you may encounter in the published literature or theorize in your own research. Space precludes a detailed discussion of more complex models, and understandably, given how no attention has been dedicated to the statistical analysis of such models in the methodology literature, more complex models are rare in the substantive literature. However, examples can be found, and the principles discussed thus far readily generalize to more complex models.

Implementation in Computing Software

Many believe that SEM is the appropriate analytical tool for conditional process analysis. Yet we have described regression analysis as the computational engine used to estimate effects that define a conditional process model. There is debate in the literature as to which method is better (e.g., Hayes, Montoya, & Rockwood, 2017; Iacobucci, Saldanha, & Deng, 2007; Pek & Hoyle, 2016). Our perspective is that each has strengths, weaknesses, and value.

Any conditional process analysis can be set up and estimated using SEM software, but some SEM programs make a conditional process analysis easier than do others. When using an SEM program, our preference is Mplus (L. K. Muthén & Muthén, 1998-2017) because of its built-in bootstrapping procedure and ability to construct new parameters that are functions of others in the model. This is important because inference about moderation of mediation requires combining information across two or more equations defining the model, and not all SEM programs can do this. Example Mplus code for a variety of conditional process models can be found in assorted journal articles and books (e.g., Hayes, 2015; Hayes & Preacher, 2013; B. O. Muthén, Muthén, & Asparouhov, 2016; Sardeshmukh & Vandenberg, 2017). Resources regularly appear online as well.

The biggest struggle you are likely to have when implementing a conditional process analysis in an SEM environment is the translation of the model into a corresponding code. This obstacle is eliminated with the PROCESS macro available for SPSS and SAS (Hayes, 2018a), downloadable at no cost from www.processmacro.org. Because it is so easy to use, it has become the method of choice in many disciplines. PROCESS typically produces the same results as an SEM program will generate with far less work and without requiring any knowledge of SEM (Hayes et al., 2017). PROCESS has dozens of conditional process models preprogrammed, including most of the models depicted in Figures 1 to 4 as well as many others. The user simply chooses a preprogrammed model (available in the PROCESS documentation in Appendix A of Hayes, 2018a) and tells PROCESS what variables in the data are playing what roles in the model (i.e., mediator, moderator, independent and dependent variable, covariate). Only a single line of code is necessary to estimate even the more complicated conditional process models we have discussed. PROCESS estimates model coefficients, produces bootstrap inference for conditional indirect effects and tests of moderated/partial/conditional/moderated mediation, can conduct comparisons between conditional indirect effects, and calculate various other statistics. In the event the user's desired model is not preprogrammed, a custom model can be programmed in a single command line, with a budget of up to two moderators and up to six mediators arranged in parallel, serial, or blended form.

One of the limitations of PROCESS is that it is restricted to observed variable models, meaning that variables are assumed to be measured with perfect reliability. This is an assumption that most social scientists make when using regression analysis and observed variable SEM. But measurement error in the variables in a linear model can produce biased estimates of effects or decrease statistical power of tests (or both). Some skeptics of observed variable conditional process analysis will lob this criticism of the use of a modeling tool like PROCESS (e.g., Cheung & Lau, 2017) even though these same critics seem perfectly comfortable using regression analysis in their own work in spite of this limitation. It is not likely that we will see a moratorium on regression analysis anytime in the future, so we see no compelling argument to stop using

PROCESS for conditional process analysis because it shares some of the flaws of linear regression analysis.

Nevertheless, SEM programs do provide options for dealing with random measurement error in more sophisticated ways than assuming it to be absent. The conditional process model specifies the structural component of the model linking latent variables, and measurement error is handled using multiple indicators for each latent variable or single-indicator latent variable approaches with a correction for measurement error (see, e.g., Kline, 2005). Latent variable conditional process analysis is relatively rare in practice, but some guidance is available (see, e.g., Hayes & Preacher, 2013; Sardeshmukh & Vandenberg, 2017). But even when such a model is properly programmed, latent variable interactions can be difficult to estimate in SEM software, and most will find this challenging. As a result, many will feel that the potential bias caused by measurement error when a tool like PROCESS is used (see, e.g., Cheung & Lau, 2017) is a reasonable price to pay for the convenience it offers.[4]

The difficulty in estimating latent variable interactions goes away if the moderator in a conditional process model is categorical. In that case, multiple group SEM can be an effective approach. This involves estimating a mediation process simultaneously in separate groups and testing the relative of fit of models that constrain indirect effects to be the same versus different across the groups (see Zenker, von Wallpach, Braun, & Vallaster, 2019, for an example). This is much simpler than estimating latent variable interactions. As a result, the temptation is strong when a moderator continuous to categorize cases into groups using (often arbitrary) cut points on the continuous variable, thereby allowing a multigroup SEM approach to be used. But the dangers of artificially categorizing continuous variables prior to analysis is well documented (e.g., Rucker, McShane, & Preacher, 2015), and its pitfalls likely generalize to multiple group SEM. The advantages that come with accounting for measurement error may be offset by the disadvantages of categorization of continuous moderators.

Multilevel Conditional Process Analysis

An assumption of traditional regression analysis is that observations (e.g., people participating in the study) are independent. This assumption is violated if they are grouped, or *clustered*, in a way that results in observations from the same cluster being more similar to one another on variables being modeled than are observations in different clusters. Examples of clustering include students in the same classroom (classrooms are the clusters, observations are the kids), medical patients who share a doctor (doctors are the clusters, observations are the patients), and employees working in an organization (organizations are the clusters, employees are the observations). Longitudinal data collection also generates clustering, as repeated measurements over time on the same person can be viewed as nested within-person. Likewise, such clustering occurs when participants in an experiment provide responses to several stimuli that vary on manipulated attributes. Responses to each stimulus are nested within person. Appropriate analysis of clustered data requires modeling techniques that account for the resulting nonindependence, with multilevel modeling being a popular method.

An important concept in multilevel analysis is *measurement level*, not to be confused with "levels of measurement" (i.e., nominal, ordinal, interval, and ratio). In a two-level multilevel model (the only type of model we discuss), measurements can occur at Level 1 or at Level 2. A Level-1 measurement is an attribute of a person nested in a particular cluster. For example, in a study that involves 10 classrooms of students, any measurement taken on *each* of the students, such as performance on a test or the child's sex, would be a Level-1 variable. A Level-2 variable is an attribute that applies to all the Level-1 observations nested in a particular cluster, such as the sex of a child's teacher. All children in Mrs. Coutts's class have a female teacher, whereas all children in Mr. Montoya's class have a male teacher. A teacher's sex does not vary within a classroom, but it can between classes. A Level-2 measurement can also be an aggregation of Level-1 measurements taken from observations in a particular cluster. For example, the mean test performance of children in Mr. Montoya's class is a Level-2 measurement, even though the test performance for a specific child is a Level-1 measurement. It is also common to use the terms *Level-1 unit* and *Level-2 unit* to refer to the observations and the clusters, respectively. So in the examples above, students, employees, and medical center patients are Level-1 units, and classrooms, companies, and doctors are Level-2 units.

As conditional process analysis has grown in popularity, so too have attempts to apply it to multilevel data problems. But the complexity of the mathematics no doubt is a deterrent to many. Examples do exist, however. For instance, in a sample of military members clustered within work units, Hannah et al. (2013) found that moral courage mediates the relationships between individual abuse from group leaders and mistreatment of noncombatants (all Level-1 variables), with the strength of the indirect effect depending on the overall amount of abusive supervision in the work unit (a Level-2 variable). Bacharach, Bamberger, and Doveh (2008), in a study of firefighters nested within companies, found that intensity of involvement in workplace critical incidents leads to distress which, in turn, elevates drinking to cope behaviors (all Level-1 variables). However, this indirect relationship was attenuated by the adequacy of company-level performance resources (a Level-2 variable).

In this section, we discuss the extension of single-level conditional process analysis to a multilevel framework, focusing only on models with X, M, and Y measured at Level 1, resulting in the so-called 1-1-1 multilevel model. Furthermore, we cover only a few conditional process models with a moderator measured at Level 2. Multilevel regression and multilevel mediation analysis have been discussed in numerous books and journal articles, and space precludes a detailed treatment of the complexities and decisions the analyst must make when theorizing and setting up a multilevel model. Beware that by its nature, the mathematics of multilevel conditional process analysis is more complicated than in the single-level analysis. We attempt to reduce the mathematics here to its bare essentials to help the reader make the jump to the more technical literature.

In a 1-1-1 multilevel mediation model, X, M and Y are measured at Level 1. In our notation, observation i in the data (e.g., an employee or a medical patient) is a member of cluster j (e.g., employed by company j, or a patient of doctor j, with that company or doctor being only one of many companies or doctors providing employees or patients as participants in the study), and his or her measurements on *X, M*, and *Y* are X_{ij}, M_{ij}, and Y_{ij}. In cluster *j*, we can estimate the *within-cluster* effects of *X* on *M, M* on *Y*, and the direct effect of *X* on *Y* using two Level-1 equations:

$$M_{ij} = d_{M_j} + a_{W_j}\tilde{X}_{ij} + e_{M_{ij}} \tag{29}$$

$$Y_{ij} = d_{Y_j} + c'_{W_j}\tilde{X}_{ij} + b_{W_j}\tilde{M}_{ij} + e_{Y_{ij}}, \tag{30}$$

where $\tilde{X}_{ij}$ and $\tilde{M}_{ij}$ are within-cluster mean-centered transformations of case *i*'s *X* and *M* values, calculated by subtracting cluster *j*'s mean on *X* and *M* from observation *i*'s *X* and *M* values (i.e., $\tilde{X}_{ij} = X_{ij} - \bar{X}_j$; $\tilde{M}_{ij} = M_{ij} - \bar{M}_j$). In Equations 29 and 30, a_{Wj}, b_{Wj}, c'_{Wj}, d_{Mj}, and d_{Yj} are the Level-1 analogues of *a, b, c', i_M*, and i_Y, respectively, in Equations 1 and 2 from a single-level mediation model. They are *within-cluster* effects.

A multilevel mediation model also contains a set of Level-2 equations that model the Level-1 coefficients as a function of Level-2 variables and cluster-specific components:

$$d_{M_j} = d_M + a_B\bar{X}_j + u_{M_j} \tag{31}$$

$$d_{Y_j} = d_Y + c'_B\bar{X}_j + b_B\bar{M}_j + u_{Y_j} \tag{32}$$

$$a_{W_j} = a_W + u_{a_j} \tag{33}$$

$$b_{W_j} = b_W + u_{b_j} \tag{34}$$

$$c'_{W_j} = c'_W + u_{c'_j}, \tag{35}$$

where $\bar{X}_j$ and $\bar{M}_j$ are the means of *X* and *M* in cluster *j* (e.g., the mean of *X* and *M* for all employees from company *j* or patients of doctor *j*). The Level-2 analogues of *a, b*, and *c'* in Equations 1 and 2 are a_B, b_B, and c'_B, respectively, in Equations 31 and 32. These are the effects of *X* and *M* at Level-2, or *between-cluster effects*. In Equations 33 to 35, the within-cluster effects are allowed to vary between clusters with the inclusion of u_{a_j}, u_{b_j}, and $u_{c'_j}$, which capture deviation between cluster *j*'s effect and an average within-cluster effect across Level-2 units, where the average within-cluster effects are denoted as a_W, b_W, and c'_W. So combined, Equations 29 to 35 provide estimates of the effect of *X* on *M, M* on *Y*, and the direct effect of *X* within a Level-2 unit (within-cluster effects) as well as between Level-2 units (between-cluster or Level-2 effects).

In this model, there are both within-cluster and between-cluster indirect effects of X on Y through M. The *between-cluster indirect effect* is $a_B b_B$. It is the effect of the cluster means of X on the cluster means of Y via the cluster means of M. Because the within-cluster effects of X and M can be specified as varying across Level-2 units, the within-cluster indirect effect can also vary across Level-2 units. It is the *average* within-cluster indirect effect that is typically of most substantive interest, defined as $a_W b_W + \sigma_{a,b}$, where $\sigma_{a,b}$ is the *covariance* between the random effects of X on M and of M on Y (Bauer, Preacher, & Gil, 2006; Kenny, Korchmaros, & Bolger, 2003). If either a or b at Level 1 is fixed to be the same across Level-2 clusters by removing either u_{a_j} or u_{b_j} from Equations 33 or 34, then $\sigma_{a,b} = 0$, and so the average within-cluster indirect effect reduces to $a_W b_W$.

In a single-level mediation analysis, bootstrapping is typically used to construct confidence intervals for the indirect effect. In the multilevel framework, it is not clear how to bootstrap to produce such a confidence interval, given that one could bootstrap sample the clusters, observations within clusters, or some combination (see Van der Leeden, Meijer, & Busing, 2008, for a discussion). An alternative method is an MCCI, computed by simulating data from the assumed forms of the sampling distributions of the estimated parameters that make up the indirect effect. In each simulation draw, the indirect effect is computed and saved. After many draws (typically 5,000+), the saved indirect effects serve as an empirical representation of the sampling distribution of the indirect effect, and MCCIs can be computed using percentiles of the Monte Carlo distribution estimates. See Preacher and Selig (2012) and Rockwood and Hayes (in press) for a more detailed discussion of the mechanics.

Adding a Level-2 Moderator

If a potential moderator is measured at Level 2, it can be included as a predictor of a within-cluster effect to explain some of the variability in that effect across Level-2 units. This moderator can operate on the effect of X on M, on the effect of M on Y, or on both.

First-Stage Model. Suppose W is a Level-2 variable hypothesized to moderate the within-cluster effect of X on M (i.e., a_{W_j}), but the effect of M on Y is fixed to be independent of W. The result is a first-stage multilevel conditional process model (as in Figure 1, panel C, with W measured at Level 2 and the other variables measured at Level 1). For example, M. Li, Perez-Diag, Mao, and Petrides (2018) report a study examining the relationship between teacher emotional intelligence and job performance in hundreds of primary school teachers (the Level-1 unit) working in one of 37 schools (the Level-2 unit) in China. They found that teacher emotional intelligence (X) influenced job performance (Y) through the effect of emotional intelligence on job satisfaction (M), which influenced performance. But this positive indirect effect was larger in schools that had earned greater emotional trust from its teachers (W) because school-level organizational trust moderated the effect of emotional intelligence on job satisfaction.

In this type of multilevel conditional process analysis, the model for a_{W_j} in Equation 33 is expanded to include W_j as a predictor. When doing so, we recommend that W be included in the equation for the Level-1 intercept in the model of M as well, resulting in the following modifications to Equations 31 and 33:

$$d_{M_j} = d_M + a_B \bar{X}_j + gW_j + u_{M_j}$$

$$a_{W_j} = a_{W0} + a_{W1} W_j + u_{a_j}. \tag{36}$$

In Equation 36, a_{W1} captures the relationship between W and the size of the within-cluster effect of X on M, and a_{W0} is the within-cluster effect of X on M for clusters with $W = 0$. The remaining component, u_{aj}, captures cluster-level differences in a_{W_j} not explained by W.

As in single-level models, the within-cluster indirect effect is the product of the effect of X on M and the effect of M on Y. For this model, the (average) conditional within-cluster indirect effect is

$$\left(a_{W0} + a_{W1} W_j\right) b_W + \sigma_{a,b} = a_{W0} b_W + a_{W1} b_W W_j + \sigma_{a,b} \tag{37}$$

where $\sigma_{a,b}$ is the residual covariance of a_{W_j} and b_{W_j}. Notice that the within-cluster indirect effect is a linear function of W. Two clusters that differ by one unit on W are expected to differ by $a_{W1} b_W$ units on the within-cluster indirect effect of X on Y through M. Thus, $a_{W1} b_W$ in Equation 37 quantifies the moderation of the within-cluster indirect effect. It is the *within-cluster index of moderated mediation*. A test of moderation of mediation by W in this model is undertaken using MCCI for $a_{W1} b_W$.

Evidence of moderation of the within-cluster indirect effect can be followed up by probing that moderation, estimating the within-cluster indirect effect at various values of W. Recall that $a_{W0} b_W$ quantifies the indirect effect when $W = 0$. W can be centered any value prior to model estimation so that $a_{W0} b_W$ estimates the conditional indirect effect when W is equal to that specific value, with an MCCI used for inference. Repeating with different values of W results in various estimates of and inferences about the conditional within-cluster indirect effect.

In addition to the within-cluster indirect effect being moderated by W, so too may be the between-cluster indirect effect. Recall that the between-cluster effect of X is modeled using the group means of X in the equations for the within-cluster constants. The equation for the intercept in the model of M (Equation 31) can be modified to allow for this effect to be a linear function of W:

$$\begin{aligned} d_{M_j} &= d_M + \left(a_{B0} + a_{B1} W_j\right) \bar{X}_j + gW_j + u_{M_j} \\ &= d_M + a_{B0} \bar{X}_j + a_{B1} W_j \bar{X}_j + gW_j + u_{M_j}. \end{aligned} \tag{38}$$

In Equation 38, a_{B1} quantifies the change in the effect of $\bar{X}_j$ on M as W changes. Since $\bar{X}_j$ contains the between-cluster differences, W is a moderator of the between-cluster effect. The between-cluster indirect effect then varies as a function of W:

$$\left(a_{B0} + a_{B1}W_j\right)b_B = a_{B0}b_B + a_{B1}b_BW_j \tag{39}$$

The *between-cluster index of moderated mediation* for this model, which quantifies the moderation of the between-cluster indirect effect, is $a_{B1}b_B$ in Equation 39. As with the within-cluster index, a MCCI can be constructed for inference.

Second-Stage Model. A similar modeling logic applies to the second-stage model with a single moderator W. In a second-stage model, the within-cluster effect of M on Y (i.e., b_{W_j}) is specified as moderated by W and the effect of X on M is fixed to be independent of W (as in Figure 1, panel D, with W as a Level-2 variable and X, M, and Y as Level-1 variables). For example, in a study of 214 families with a member with HIV (the Level-2 unit), family members' (the Level-1 unit) individual-level stress (X) indirectly influenced their psychological distress (Y) through avoidant coping (M), with this indirect effect being larger among families feeling more stress (W) as a result of the moderation of the effect of avoiding coping on psychological distress by family-level stress.

In this model, starting with Equations 29 to 35, Equations 32 and 34 are modified to allow W to moderate the within-cluster effect of M on Y and the within-cluster intercept in the model of Y:

$$d_{Y_j} = d_Y + c'_B\bar{X}_j + b_B\bar{M}_j + gW_j + u_{Y_j} \tag{40}$$

$$b_{W_j} = b_{W0} + b_{W1}W_j + u_{b_j}.$$

The average within-cluster indirect effect is the product of the within-cluster effect of X on M and the conditional within-cluster effect of M on Y

$$a_W\left(b_{W0} + b_{W1}W_j\right) + \sigma_{a,b} = a_Wb_{W0} + a_Wb_{W1}W_j + \sigma_{a,b}, \tag{41}$$

which is a linear function of W. The weight for W in Equation 41, a_Wb_{W1}, quantifies the moderation of the within-cluster indirect effect. It is the within-cluster index of moderated mediation for this model. A MCCI can be used for inference, and probing can be undertaken as described for the first-stage model by centering W around various values and reestimating the model.

If one also desires the between-cluster effect of M on Y to be moderated by W, instead of Equation 40, use

$$d_{Y_j} = d_Y + c'_B \bar{X}_j + b_{B0} \bar{M}_j + gW_j + b_{B1} \bar{M}_j W_j + u_{Y_j}$$

such that b_{B1} quantifies the change in the effect of $\bar{M}_j$ on Y as W changes. The between-cluster indirect effect of X then varies as a function of W:

$$a_B \left(b_{B0} + b_{B1} W_j \right) = a_B b_{B0} + a_B b_{B1} W_j. \quad (42)$$

The between-cluster index of moderated mediation quantifying the moderation of the between-cluster indirect effect is $a_B b_{B1}$ in Equation 42. A MCCI can be constructed for this index to test for moderation of the between-cluster indirect effect of X.

First- and Second-Stage Model. The first- and second-stage multilevel conditional process model has a common Level-2 moderator (as in Figure 1, panel E, with W as a Level-2 variable and X, M, and Y as Level-1 variables) of the first- and second-stage effects at Level 1. For example, on each of 5 days during a work week, Wheeler, Halbeslen, and Whitman (2013) assessed the extent to which an employee felt abused by his or her supervisor (X) and emotionally exhausted (M), as well as the extent to which one of his or her coworkers felt abused by the employee (Y). In the analysis, the repeated measurements of X, M, and Y are the Level-1 units. Each employee, the Level-2 unit, was measured on psychological entitlement (W). Their model allowed the indirect effect of abusive supervision on coworker abuse through emotional exhaustion to be moderated by psychological entitlement, with entitlement moderating the effect of abusive supervision on exhaustion as well as exhaustion on coworker abuse.

This model requires a combination of the mathematics described earlier for the first- and the second-stage models. Assuming that both the within- and the between-cluster effects of X on M and M on Y are specified as moderated by Level-2 moderator W, the Level-1 equations are

$$M_{ij} = d_{M_j} + a_{W_j} \tilde{X}_{ij} + e_{M_{ij}}$$

$$Y_{ij} = d_{M_j} + c'_{W_j} \tilde{X}_{ij} + b_{W_j} \tilde{M}_{ij} + e_{Y_{ij}},$$

and the Level-2 equations are

$$d_{M_j} = d_M + a_{B0} \bar{X}_j + a_{B1} W_j \bar{X}_j + g_M W_j + u_{M_j},$$

$$d_{Y_j} = d_Y + c'_B \bar{X}_j + b_{B0} \bar{M}_j + g_Y W_j + b_{B1} \bar{M}_j W_j + u_{Y_j},$$

$$a_{W_j} = a_{W0} + a_{W1}W_j + u_{a_j},$$

$$b_{W_j} = b_{W0} + b_{W1}W_j + u_{b_j},$$

and

$$c'_{W_j} = c'_W + u_{c'_j}. \tag{43}$$

The within-cluster indirect effect is the product of the within-cluster conditional effect of X on M and the within-cluster conditional effect of M on Y:

$$\left(a_{W0} + a_{W1}W_j\right)\left(b_{W0} + b_{W1}W_j\right) + \sigma_{a,b} = a_{W0}b_{W0} + (a_{W0}b_{W1} + a_{W1}b_{W0})W_j + a_{W1}b_{W1}W_j^2 + \sigma_{a,b}$$

(Bauer et al., 2006), which is a nonlinear function of W unless W is dichotomous. There is no index of moderated mediation for this model when W is continuous. The between-cluster indirect effect of X in this model is

$$\left(a_{B0} + a_{B1}W_j\right)\left(b_{B0} + b_{B1}W_j\right) = a_{B0}b_{B0} + (a_{B0}b_{B1} + a_{B1}b_{B0})W_j + a_{B1}b_{B1}W_j^2,$$

which is also a nonlinear function of W.[5]

Moderation of the Direct Effect of X

Thus far, we have neglected moderation of the direct effect of X. In any of the three models we discussed, W can be included in the model of the Level-1 direct effect of X (Equations 35 and 43) as such:

$$c'_{W_j} = c'_{W0} + c'_{W1}W_j + u_{c'_j}. \tag{44}$$

The weight for W in Equation 44, c'_{W1}, quantifies the relationship between W and the within-cluster direct effect of X. The between-cluster direct effect can also be modeled as a linear function of W by including $W_j\overline{X}_j$ as a predictor in the model for d_{Yj}, where the corresponding coefficient quantifies the relationship between W and the between-cluster direct effect of X.

Implementation in Statistical Software

Multilevel conditional process analysis can be implemented using multilevel or mixed modeling procedures implemented in most standard software programs. These include the MIXED procedures in SPSS and SAS as well as the lme4 package in R (Bates, Maechler, Bolker, & Walker, 2015). If the covariance between the within *a* and *b* paths is not modeled, the *M* and *Y* models can be fit separately. If this covariance is estimated, the equations need to be fit jointly (i.e., simultaneously) using the method described by Bauer et al. (2006) and Rockwood (2017). However, this procedure can be tedious to implement even for simple multilevel mediation models. Furthermore, special computational tools are needed to estimate MCCI confidence intervals for indirect effects and the indices of moderated mediation.

PROCESS, described earlier, does not do multilevel analysis. An alternative for multilevel conditional process analysis in SPSS is the MLMED macro (downloadable from www.njrockwood.com; Rockwood, 2017). Although MLMED is currently limited to a small subset of possible conditional process models (including the three we described here, see the User Guide for full details on the available models), it massively reduces the data manipulation and code required in other software platforms to only a single line of code. MLMED automatically decomposes Level-1 predictors into within- and between-cluster components; calculates within and between indirect effects, the index of moderated mediation; generates MCCIs for the index and conditional indirect effects; and organizes the results neatly by equation and level of analysis.

For more complex multilevel conditional process models, some SEM programs can be used, with Mplus being the most comprehensive. The MLM implementation within Mplus is typically referred to as *multilevel structural equation modeling* (MSEM), which is an extension of MLM for fitting models with multivariate responses (e.g., mediation and conditional process models), Level-2 response variables (e.g., where *M* or *Y* is a Level-2 variable), measurement error (by using a factor model equivalent to that in single-level SEM), and more flexible random effect covariance matrices. Another advantage of the MSEM framework is the ability to *latent mean center* Level-1 predictors, where the cluster means are modeled as latent variables. This eliminates measurement error within the cluster means, which can bias between-cluster effects (Lüdtke et al., 2008). Although there are no major resources regarding conditional process modeling within the MSEM framework, Preacher, Zypher, & Zhang (2010) and Preacher, Zhang, & Zypher (2016) provide excellent resources for the building blocks (e.g., mediation and moderation). The methods we have described here can be adapted to the MSEM framework. It should be noted, however, that computational difficulties, including long estimation times and nonconvergence, may result from the greater flexibility of the MSEM framework, depending on the specific model of interest. Future advancements in estimation and computing should eventually minimize such difficulties.

Summary

Research in the behavioral sciences has been moving away from merely establishing that effects exist and their boundary conditions. We increasingly are dedicating research efforts to understanding the mechanisms by which effects operate and the factors that influence the size or strength of those mechanisms. Conditional process analysis is a large analytical umbrella that encompasses many kinds of methods and analytical approaches useful for understanding the contingencies of mechanisms, most of which we did not address here. In this article, we discussed some forms that conditional process models can take, limiting our discussion to how such models can be estimated using linear regression analysis in single or multilevel form. We overviewed some of the fundamental computational principles and offered some advice on interpretation and implementation. We also addressed more complicated models that involve more than one mediator or more than one moderator and discuss some computational options to simplify the analysis. It will take more than this overview of fundamentals and advances to become fluent in the methods we discussed. But we hope the guidance that we have offered and our heavy referencing of examples and sources will both help you better understand how you can test complicated theories about the contingencies of mechanisms and stimulate your future thinking and theorizing now knowing what is analytically possible.

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Notes

1. It is a widespread myth that mean centering or standardizing X and W is necessary prior to the estimation of Equation 3. Doing so will not affect the test of moderation, the computation of conditional effects of X, or any of the computational principles that we describe in this article. See Hayes (2018a) for a discussion.
2. Contrary to guidelines offered by some (e.g., Muller et al., 2005), the regression weight for XW in Equation 5 need not be statistically significant, nor need it be the regression coefficient for M in Equation 6. Neither of these quantify the relationship between the indirect effect and the moderator. It is inference about their product—the index of moderated mediation—that directly tests moderation of the indirect effect. See Hayes (2015, 2018a) for a discussion.
3. If W is a dichotomous variable with the groups coded $W = w_1$ and $W = w_2$, the difference between the indirect effects of X in the two groups is $a_1b_3\left(w_1 - w_2\right) + a_3b_1\left(w_1 - w_2\right) + a_3b_3\left(w_1^2 - w_2^2\right)$. A bootstrap confidence interval for this difference can be used as a test of moderation of mediation in the first- and second-stage conditional process model.
4. The features of PROCESS and SEM programs such as Mplus evolve over time. Our discussion captures only the relative advantages and disadvantages of PROCESS compared with SEM approaches at this point in time.
5. When W is dichotomous, with the two groups coded as $W = w_1$ and $W = w_2$, the difference between the average within-cluster indirect effects in the two groups is

$a_{W0}b_{W1}(w_1 - w_2) + a_{W1}b_{W0}(w_1 - w_2) + a_{W1}b_{W1}(w_1^2 - w_2^2)$. The difference between the two between-cluster indirect effects is $a_{B0}b_{B1}(w_1 - w_2) + a_{B1}b_{B0}(w_1 - w_2) + a_{B1}b_{B1}(w_1^2 - w_2^2)$. These are both indices of moderated mediation for this model when W is dichotomous.

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