On the Moderation of Mechanisms: A Conceptual Overview of Conditional Process Analysis

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These are slides at:

www.afhayes.com/public/mobc.pdf

I will ☑ and will not ☐

- ☑ … do a brief review of the analysis of indirect and conditional effects.
- ☑ … do a conceptual introduction to "conditional process analysis."
- ☑ … define the conditional indirect and direct effect.
- ☑ … do one simple example, with relevant computer output.
- ☑ … talk about some interesting extensions of basic principles
- ☑ … speak mostly in abstractions. You can fill in the blanks concretely.
- ☐ … turn you into a conditional process analysis expert.
- ☐ … teach you how to estimate such models in your chosen software.
- ☐ … get all your questions answered.
- ☑ … leave you with many new questions unanswered.
- ☑ … point you toward where you can learn more.

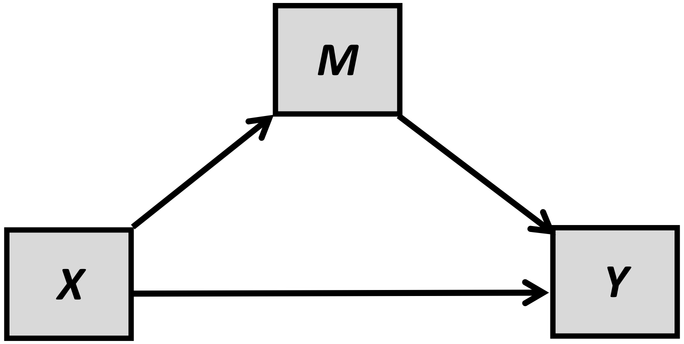
My objective is primarily to whet your appetite for learning more. **Knowing what is possible analytically can influence how we think about problems theoretically.**

What is "Conditional Process Analysis"

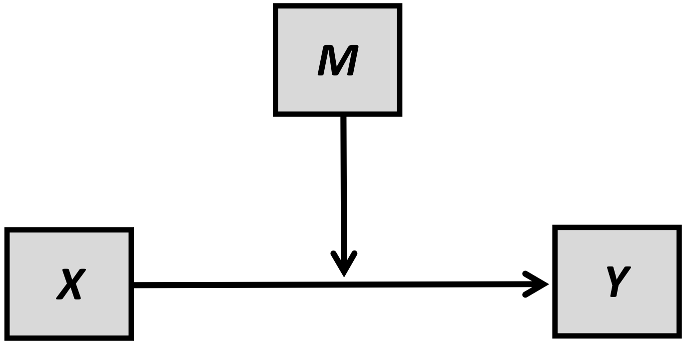
"Conditional process analysis" is a modeling strategy undertaken with the goal of **describing the *conditional* or *contingent* nature of the *mechanism*(*s*) by which a variable transmits its effect on another, and testing hypotheses about such contingent effects**.

A melding of two ideas conceptually and analytically:

"**Process analysis**", used to quantify and examine the direct and indirect pathways through which an antecedent variable *X* transmits its effect on a consequent variable *Y* through an intermediary *M*. Better known as "mediation analysis" these days.



"**Moderation analysis**" used to examine how the effect of an antecedent *X* on an consequent *Y* depends on a third moderator variable *M* (a.k.a. "interaction")

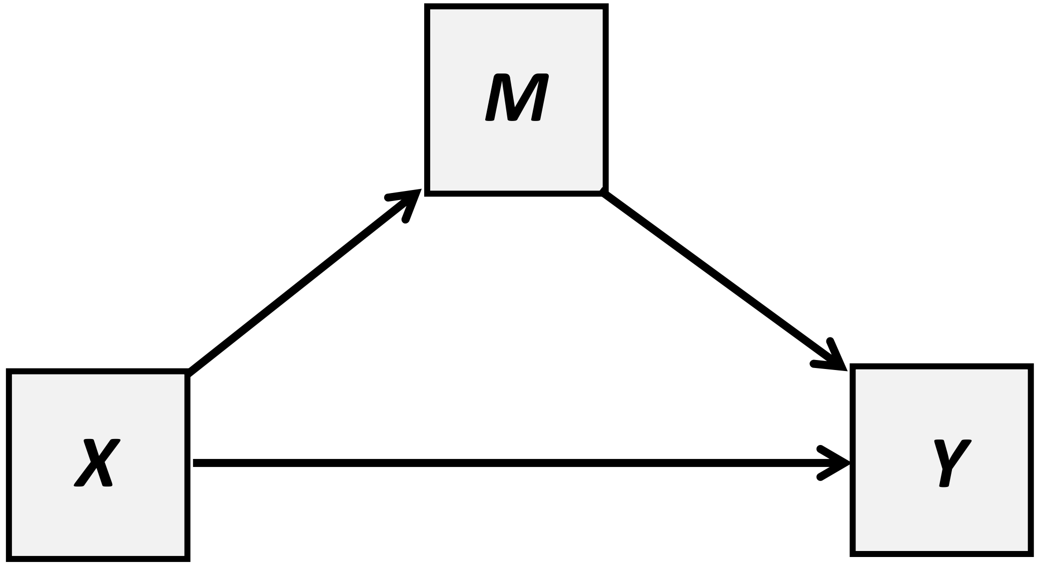


Mechanisms are quantified with indirect effects. Indirect effects can be moderated, meaning mechanisms can be contingent. We can model such contingencies using rudimentary linear modeling principles. It is not difficult once you learn the fundamentals.

Mediation

A mediation model links a putative cause (*X*) to a presumed effect (*Y*) at least in part through an intermediary or "mediator" variable (*M*).

The "simple mediation" model

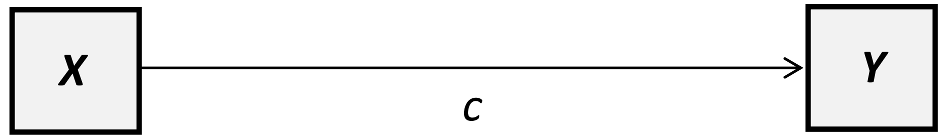


X→*M*→*Y* is a causal chain of events. A mediator variable can be a psychological state, a cognitive process, an affective response, a biological change, or any other conceivable "mechanism" variable through which *X* exerts an effect on *Y*. *But it must be causally between X and Y.*

“Indirect effect”

Using OLS or ML, with *Y* as continuous:

$$\hat{Y} = i_1 + cX$$

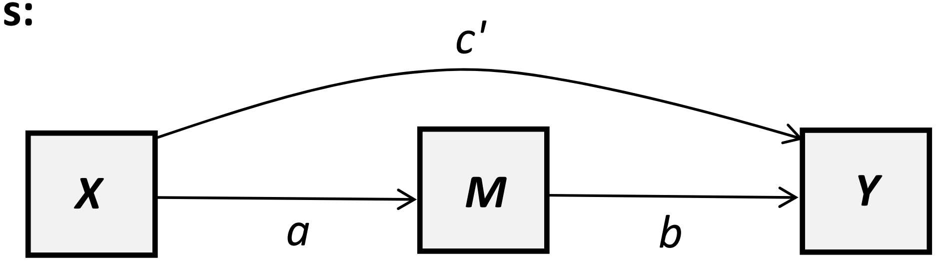


c = “total effect” of X on Y

Using OLS or ML, with *M* as continuous:

$$\hat{M} = i_2 + aX$$

$$\hat{Y} = i_3 + c'X + bM$$



c' = “direct effect” of X on Y

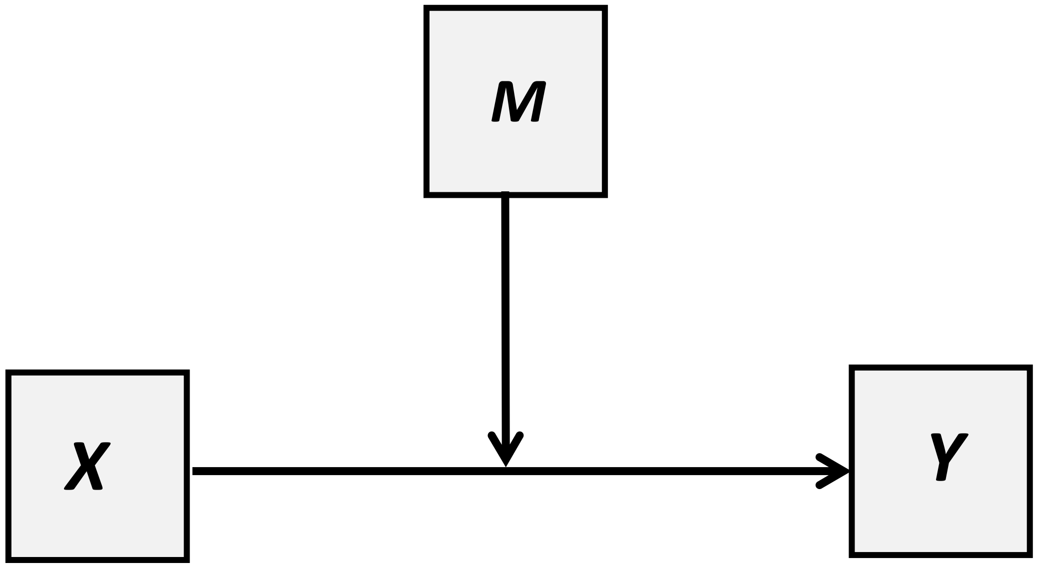
ab = “indirect effect” of X on Y through M

$c = c' + ab$

The indirect effect quantifies the effect of X on Y through M. Evidence that ab is different from zero is consistent with mediation. Evidence that path c is different from zero is **not** a requirement of 21st century mediation analysis. Correlation between X and Y is neither sufficient **nor necessary** to claim that X affects Y.

Moderation

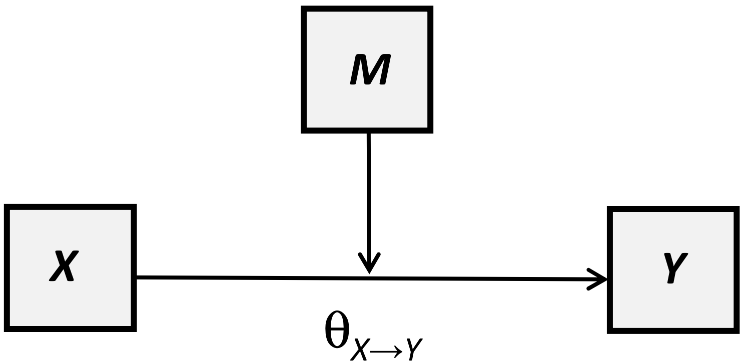
Moderation. The effect of *X* on *Y* can be said to be *moderated* if its size or direction is dependent on *M*. It tells us about the conditions that facilitate, enhance, or inhibit the effect, or for whom or what the effect is large vs. small, present versus absent, and so forth.



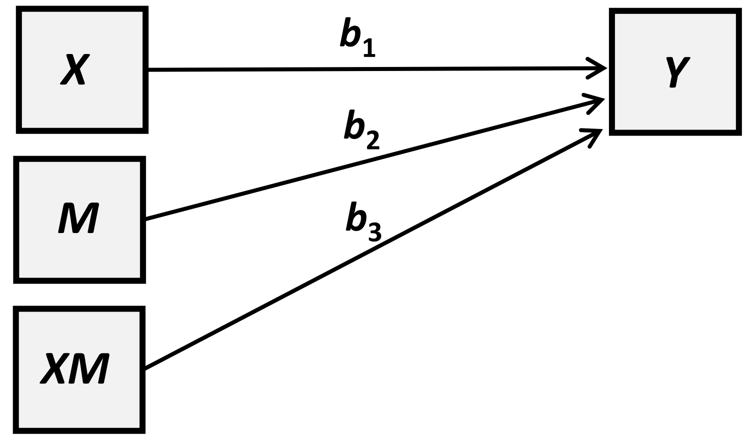
M is depicted here to *moderate* the size of the effect of *X* on *Y*, meaning that the size of the effect of *X* on *Y* depends on *M*. We say *M* is the *moderator* of the $X \rightarrow Y$ relationship, or *X* and *M* *interact* in their influence on *Y*.

"Linear moderation" and "Conditional effect"

Conceptual diagram depicting *X*'s effect on *Y* moderated by *M*.



Linear moderation as a statistical model



"Simple linear moderation" is typically estimated by allowing *X*'s effect on *Y* to be a linear function of *M* (other forms of moderation are possible):

$$\hat{Y} = i_1 + (b_1 + b_3 M)X + b_2 M = i_1 + b_1 X + b_2 M + b_3 XM$$

In this model, the *conditional effect* of *X* on *Y*, $\theta_{X\rightarrow Y}$, is $b_1 + b_3 M$:

$$\hat{Y} = i_1 + \theta_{X\rightarrow Y} X + b_2 M \quad \text{where} \quad \theta_{X\rightarrow Y} = b_1 + b_3 M$$

There is no effect of *X* on *Y* that one can reduce to a single estimate, for the effect of *X* on *Y* depends on *M* unless b_3 is zero. An inference about the coefficient for *XM* in the model is a widely used test of linear moderation.

Integrating mediation and moderation analysis

Combining moderation and mediation analysis, at least in principle, is not new at all. Many have talked about it in the distant past (e.g., Judd & Kenny, 1981; James & Brett, 1984; Baron and Kenny, 1986). It goes by various names that often confuse, including "moderated mediation" and "mediated moderation."

More recently:

Muller, Judd, and Yzerbyt (2005): Describe analytical models and steps for assessing when "mediation is moderated" and "moderation is mediated."

Edwards and Lambert (2007): Take a path analysis perspective and show how various effects in a simple mediation model can be conditioned on a third variable.

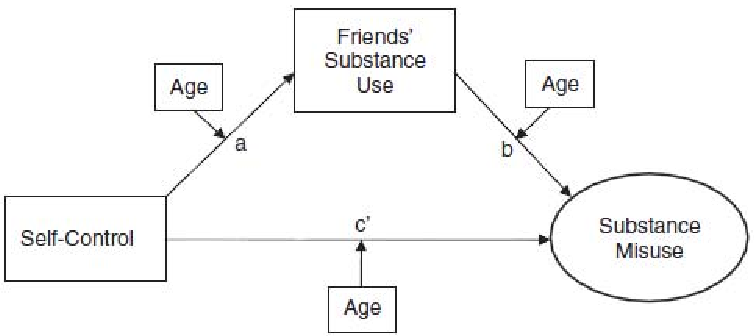
Preacher, Rucker, and Hayes (2007): Provide a formal definition of the *conditional indirect effect* and give formulas, standard errors, and a bootstrap approach for estimating and testing hypotheses about moderated mediation in five different models.

MacKinnon and colleagues (e.g., Fairchild & MacKinnon, 2009): Explicate various analytical approaches to testing hypotheses about mediated moderation and moderated mediation.

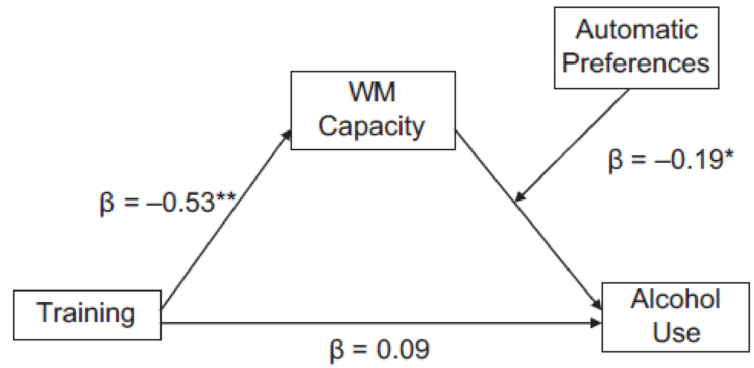
Hayes (2013) and Hayes and Preacher (2013). Introduce the term "conditional process modeling" and (in Hayes and Preacher, 2013) take a structural equation modeling approach to estimating the contingent nature of direct and indirect effects.

Examples in substance use research

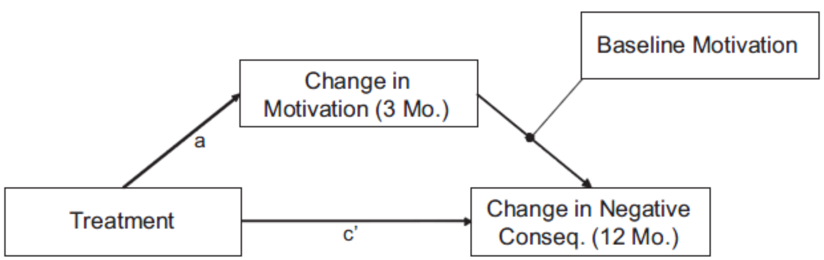
As a result of these recent discussions and the analytical approaches described therein, models that combine moderation and mediation are seen in the literature with increasing frequency, **including in alcoholism research.**



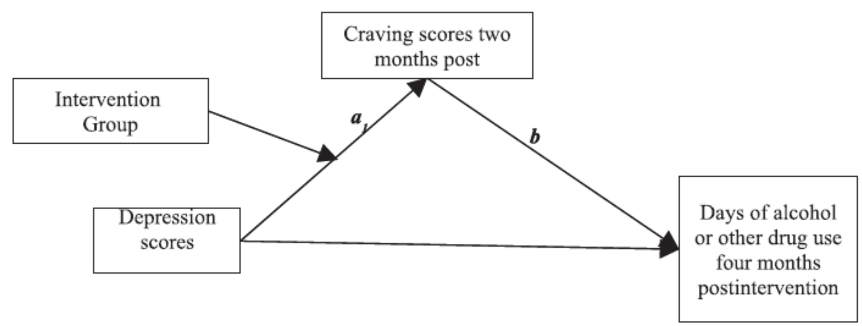
Malouf, E., Stuewig, J., & Tangney, J. (2012). Self-control and jail inmates' substance misuse post-release: Mediation by friends' substance use and moderation by age. ***Addictive Behaviors,*** *37*, 1198-1204.



Houben, K., Wiers, R. W., & Jansen, A. (2011). Getting a grip on drinking behavior: Training working memory to reduce alcohol abuse. ***Psychological Science****, 22*, 968-975.

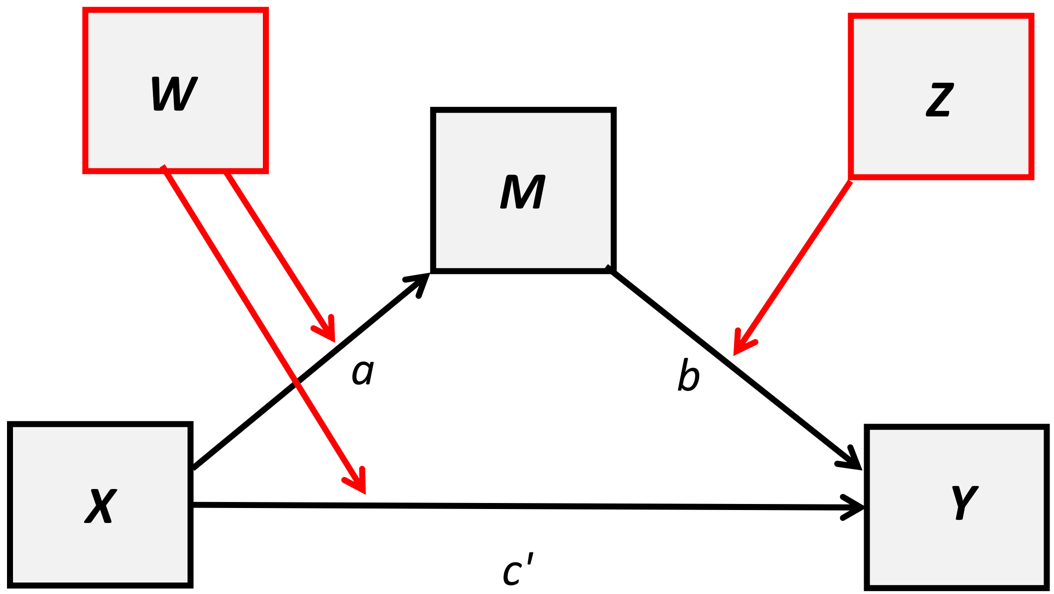


Stein, L. A. R., Minugh, P. A. et al. (2009). Readiness to change as a mediator of the effect of a brief motivational intervention on posttreatment alcohol-related consequences of injured emergency department hazardous drinkers**.** ***Psychology of Addictive Behaviors****, 23*, 185-195.



Witkiewitz, K., & Bowen, S. (2010). Depressing, craving, and substance use Following a randomized trial of mindfulness-based relapse prevention. ***Journal of Consulting and Clinical Psychology,*** *78*, 362-374.

Integrating mediation and moderation



- The indirect effect of *X* on *Y* through *M* is estimated as the product of the *a* and *b* paths
- But what if size of *a* or *b* (or both) depends on another variable (i.e., is moderated)?
- If so, then the magnitude of the indirect effect therefore depends on a third variable, meaning that "mediation is moderated".
- When *a* or *b* is moderated, it is sensible then to estimate "conditional indirect effects"—values of indirect effect conditioned on values of the moderator variable that moderates *a* and/or *b*.
- Direct effects can also be conditional. For instance, in the above, *W* moderates *X*'s direct effect on *Y*.

Example inspired by …

Witkiewitz, K., & Bowen, S. (2010). Depression, craving, and substance use following a randomized trial of mindfulness-based relapse prevention. *Journal of Consulting and Clinical Psychology, 78*, 362-374.

Journal of Consulting and Clinical Psychology
2010, Vol. 78, No. 3, 362–374

0022-006X/10/$12.00 DOI: 10.1037/a0019172

Depression, Craving, and Substance Use Following a Randomized Trial of Mindfulness-Based Relapse Prevention

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Objective: A strong relation between negative affect and craving has been demonstrated in laboratory and clinical studies, with depressive symptomatology showing particularly strong links to craving and substance abuse relapse. Mindfulness-based relapse prevention (MBRP), shown to be efficacious for reduction of substance use, uses mindfulness-based practices to teach alternative responses to emotional discomfort and lessen the conditioned response of craving in the presence of depressive symptoms. The goal in the current study was to examine the relation between measures of depressive symptoms, craving, and substance use following MBRP. ***Method:*** Individuals with substance use disorders ($N = 168$; mean age 40.45 years, $SD = 10.28$; 36.3% female; 46.4% non-White) were recruited after intensive stabilization, then randomly assigned to either 8 weekly sessions of MBRP or a treatment-as-usual control group. Approximately 73% of the sample was retained at the final 4-month follow-up assessment. ***Results:*** Results confirmed a moderated-mediation effect, whereby craving mediated the relation between depressive symptoms (Beck Depression Inventory) and substance use (Timeline Follow-Back) among the treatment-as-usual group but not among MBRP participants. MBRP attenuated the relation between postintervention depressive symptoms and craving (Penn Alcohol Craving Scale) 2 months following the intervention ($f^2 = .21$). This moderation effect predicted substance use 4 months following the intervention ($f^2 = .18$). ***Conclusion:*** MBRP appears to influence cognitive and behavioral responses to depressive symptoms, partially explaining reductions in postintervention substance use among the MBRP group. Although results are preliminary, the current study provides evidence for the value of incorporating mindfulness practice into substance abuse treatment and identifies a potential mechanism of change following MBRP.

Keywords: mindfulness based relapse prevention, substance use, craving, negative affect, depression

Addiction has generally been characterized as a chronic and relapsing condition (Connors, Maisto, & Zywiak, 1996; Leshner, 1999). Research on the relapse process has implicated numerous risk factors that appear to be the most robust and immediate predictors of posttreatment substance use, including negative affect, craving or urges, interpersonal stress, motivation, self-efficacy, and ineffective coping skills in high-risk situations (Connors et al., 1996; Witkiewitz & Marlatt, 2004). Targeting these risk factors during treatment, either pharmacologically (e.g., naltrexone to reduce alcohol craving; Richardson et al., 2008) or behaviorally (e.g., coping skills training; Monti et al., 2001), has become a priority for substance abuse researchers and clinicians.

Depression, Craving, and Relapse

The significant roles of negative affective states and craving in the substance use relapse process have been described for over 30 years (e.g., Ludwig & Wikler, 1974; Solomon & Corbit, 1974). Craving, the subjective experience of an urge or desire to use substances (Kozlowski & Wilkinson, 1987), has been shown to strongly predict reinstatement of substance use for all major drugs of abuse (e.g., Hartz, Frederick-Osborne, & Galloway, 2001; Hopper et al., 2006; Shiffman et al., 2002). Negative affect has been shown to be a prominent cue for craving in both laboratory and clinical studies (e.g., Cooney, Litt, Morse, Bauer, & Gaupp, 1997; Perkins & Grobe, 1992; Shiffman & Waters, 2004; Sinha & O'Malley, 1999; Stewart, 2000; Wheeler et al., 2008), and both the experience of negative affective states and the desire to avoid these aversive states have been described as primary motives for substance use (e.g., Wikler, 1948). Depressive symptomatology has been linked to reinitiation of drug use following periods of abstinence (e.g., Curran, Booth, Kirchner, & Deneke, 2007; Witkiewitz & Villarroel, 2009), and self-reported depression has been shown to predict substance use treatment outcomes (e.g., Cornelius et al., 2004; Greenfield et al., 1998; Hodgins, el-Guebaly, & Armstrong, 1995).

The relation between depression and substance use is also evident in the disproportionately higher rates of substance use relapse in individuals with affective disorders (Conner, Sorensen, & Leonard, 2005; Hasin & Grant, 2002; Kodl et al., 2008).

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168 clients of a public service agency providing treatment for alcohol and substance use disorders.

MBRP : Randomly assigned to treatment as usual (0) or mindfulness-based relapse prevention therapy (1)

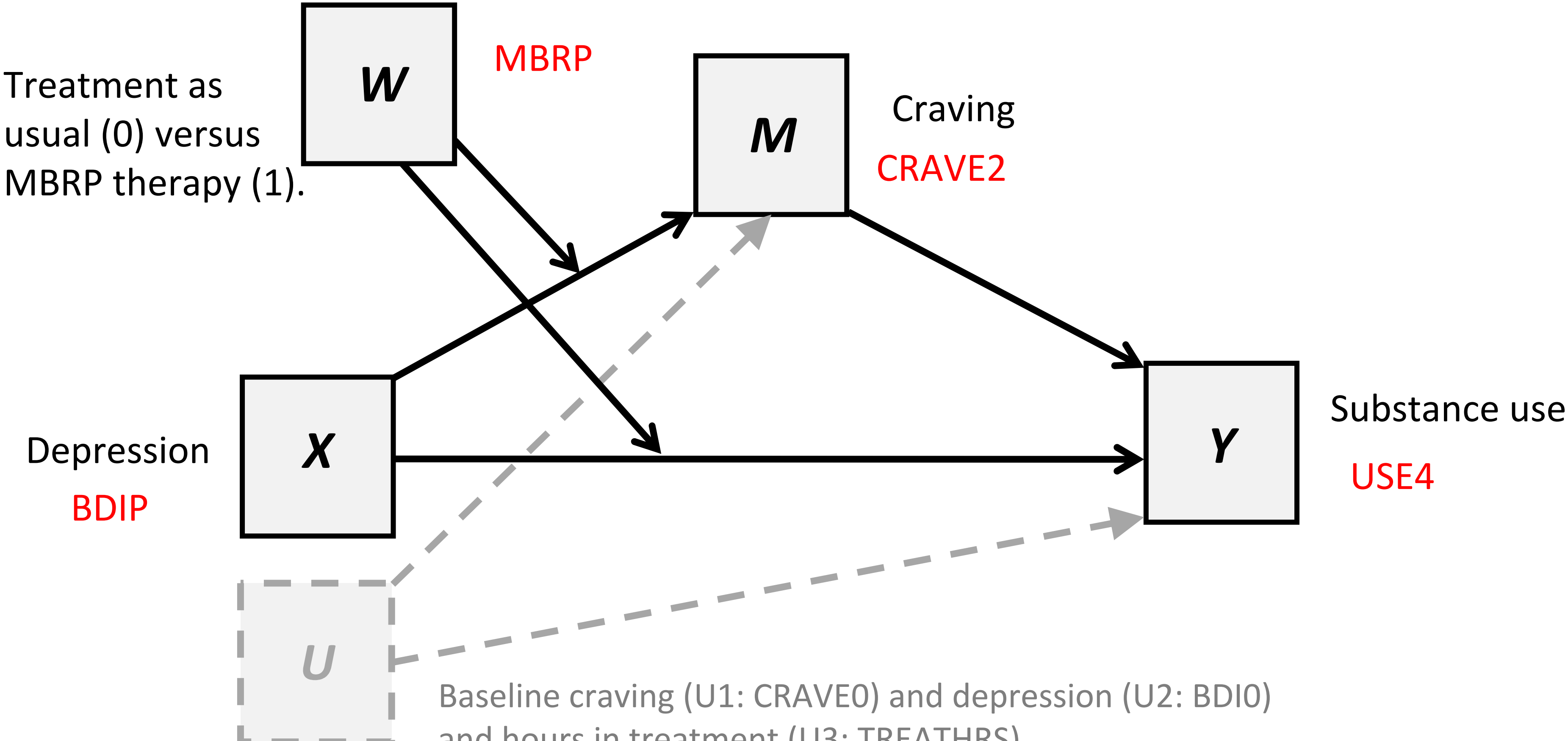
BDIP: Beck Depression Inventory scores immediately following completion of therapy.

CRAVE2: Score on the Penn Alcohol Craving Scale at 2 month follow-up.

USE4: Alcohol and other substance use at 4-month follow-up measured with the Timeline Follow-Back.

Covariates in the model included depression at start of therapy (BDI0), craving at baseline (CRAVE0) and hours in treatment (TREATHRS).

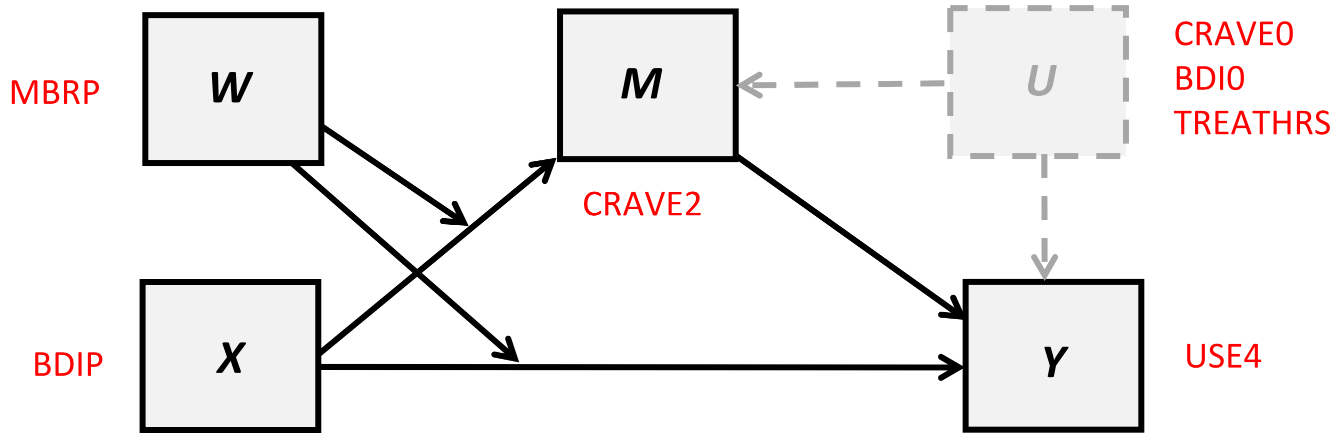
The model



Question: Do the skills acquired through MBRP therapy moderate craving as the mechanism through which negative affect influences alcohol and other substance use? This is a "first stage" moderated mediation model that also allows for the direct effect of *X* to be moderated.

The model in equation form

A conditional process model with a common moderator of the first stage path of the $X \rightarrow M \rightarrow Y$ indirect effect (the mechanism) as well as the direct effect of X on Y.



This model is estimated (using OLS, for example) as:

$$\hat{M} = i_1 + a_1 X + a_2 W + a_3 XW + \ldots$$
$$Y = i_2 + c_1' X + c_2' W + c_3' XW + bM + \ldots$$

or

equivalently

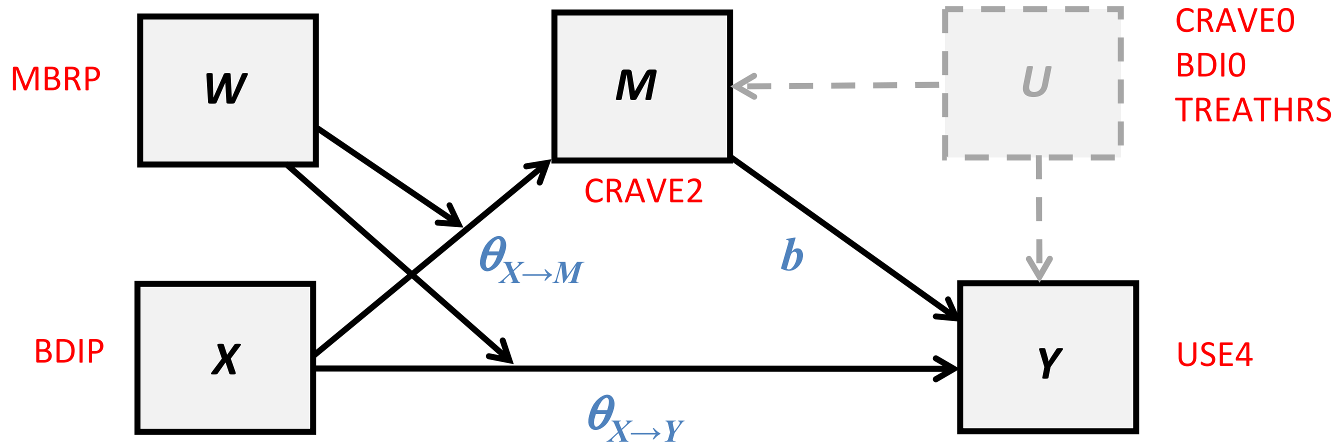
$$\hat{M} = i_1 + (a_1 + a_3 W) X + a_2 W + \ldots$$
$$\hat{Y} = i_2 + (c_1' + c_3' W) X + c_2' W + bM + \ldots$$

Using my "theta notation":

$$\hat{M} = i_1 + \theta_{X \rightarrow M} X + a_2 W + \ldots$$
$$\hat{Y} = i_2 + \theta_{X \rightarrow Y} X + c_2' W + bM + \ldots$$

where $\theta_{X \rightarrow M} = a_1 + a_3 W$ and $\theta_{X \rightarrow Y} = c_1' + c_3' W$

The conditional indirect effect



This model is estimated as:

$$\hat{M} = i_1 + a_1 X + a_2 W + a_3 XW + \ldots$$
$$Y = i_2 + c_1' X + c_2' W + c_3' XW + bM + \ldots$$

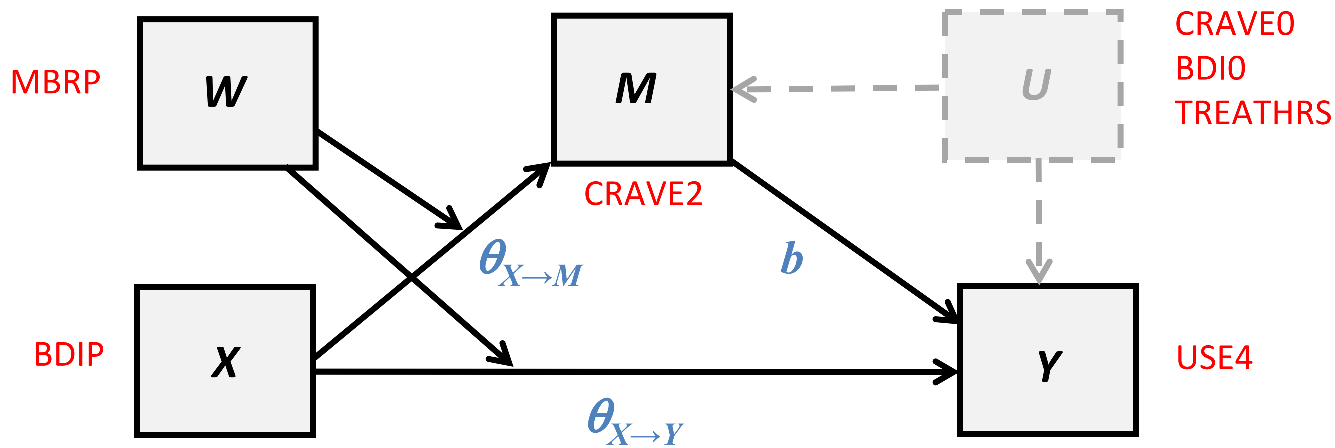
or

equivalently

$$\hat{M} = i_1 + \theta_{X\to M} X + a_2 W + \ldots$$
$$\hat{Y} = i_2 + \theta_{X\to Y} X + c_2' W + bM + \ldots$$
$$\theta_{X\to M} = a_1 + a_3 W \quad \text{and} \quad \theta_{X\to Y} = c_1' + c_3' W$$

The indirect effect of *X* on *Y* through M is the product of the effect of *X* on *M* and the effect of *M* on *Y*: $\omega_M = \theta_{X\to M} b = (a_1 + a_3 W)b = a_1 b + a_3 bW$. This is a *function* of *W*. Plug in a value of *W* and you get the "conditional indirect effect" of *X* on *Y* through *M*, conditioned on that value of *W*. An inference about that conditional indirect effect is an inference about "conditional" mediation. In this example, *W* is dichotomous, but it doesn't have to be.

The conditional direct effect



This model is estimated as:

$$\hat{M} = i_1 + a_1 X + a_2 W + a_3 XW + \ldots$$
$$Y = i_2 + c_1' X + c_2' W + c_3' XW + bM + \ldots$$

or

equivalently

$$\hat{M} = i_1 + \theta_{X\to M} X + a_2 W + \ldots$$
$$\hat{Y} = i_2 + \theta_{X\to Y} X + c_2' W + bM + \ldots$$
$$\theta_{X\to M} = a_1 + a_3 W \quad \text{and} \quad \theta_{X\to Y} = c_1' + c_3' W$$

The direct effect of *X* on *Y* through *M* is $\theta_{X\to M} = c'_1 + c'_3 W$. This is a *function* of *W*. Plug in a value of *W* and you get the "conditional direct effect" of *X* on *Y*. An inference about that conditional direct effect is an inference about whether *X* affects *Y* independent of the mechanism through *M*, conditioned on that value of *W*.

Easy to do with software you are (probably) already using

The PROCESS macro for SPSS and SAS is turn-key and easy to use but less flexible because the user is constrained to models PROCESS is programmed to estimate. PROCESS is freely available at *www.afhayes.com*

SPSS:

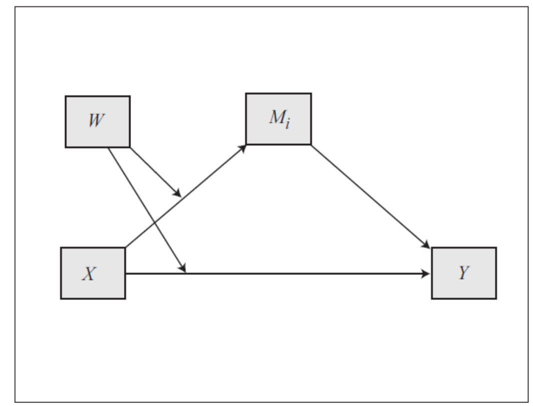
process vars=crave2 use4 bdip mbrp crave0 bdi0 treathrs/y=use4/m=crave2 /x=bdip/w=mbrp/model=8/boot=10000.

SAS:

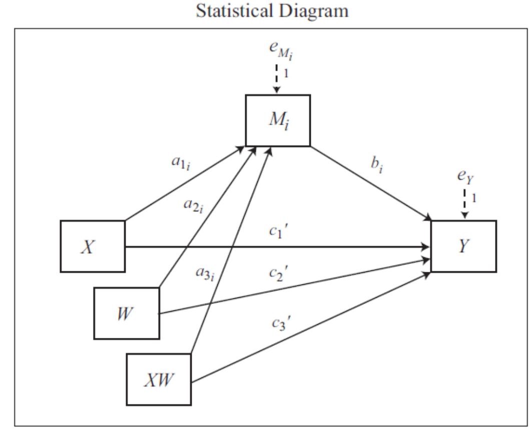
%process (data=meditate,vars=crave2 use4 bdip mbrp crave0 bdi0 treathrs, y=use4,m=crave2,x=bdip,w=mbrp, model=8,boot=10000);

Model 8

Conceptual Diagram

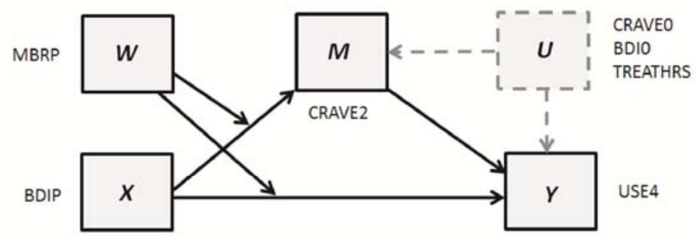


Statistical Diagram



Mplus can also be used. It requires more programming skill but is more versatile with more benefits and fewer limitations.

PROCESS output



<u>SPSS:</u>

```
process vars=crave2 use4 bdip mbrp crave0 bdi0 treathrs/y=use4/m=crave2/x=bdip
  /w=mbrp/model=8/boot=10000.
```

<u>SAS:</u>

```
%process (data=meditate,vars=crave2 use4 bdip mbrp crave0 bdi0 treathrs,y=use4,
  m=crave2,x=bdip,w=mbrp,model=8,boot=10000);
```

```
**************** PROCESS Procedure for SPSS Release 2.12 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 8
    Y = use4
    X = bdip
    M = crave2
    W = mbrp

Statistical Controls:
CONTROL= crave0   bdi0     treathrs

Sample size
        168

**************************************************************************
Outcome: crave2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5731      .3284     1.1897    13.1212     6.0000   161.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .9519      .2299     4.1404      .0001      .4979     1.4060
bdip          .0470      .0107     4.3922      .0000      .0259      .0682
mbrp         -.1874      .2374     -.7896      .4309     -.6562      .2813
int_1        -.0448      .0131    -3.4123      .0008     -.0707     -.0189
crave0        .1726      .0699     2.4697      .0146      .0346      .3106
bdi0          .0099      .0093     1.0600      .2907     -.0085      .0283
treathrs     -.0219      .0130    -1.6801      .0949     -.0476      .0038

Interactions:

 int_1    bdip        X      mbrp
```

```
**************************************************************************
Outcome: use4

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .8005      .6407   117.1381    40.7651     7.0000   160.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.8526     2.3997     2.0221      .0448      .1133     9.5918
crave2       8.1976      .7820    10.4829      .0000     6.6533     9.7420
bdip          .6503      .1124     5.7858      .0000      .4283      .8723
mbrp        11.9168     2.3598     5.0498      .0000     7.2563    16.5772
int_2        -.7604      .1349    -5.6362      .0000    -1.0268     -.4940
crave0       -.7239      .7064    -1.0248      .3070    -2.1190      .6712
bdi0         -.5489      .0928    -5.9141      .0000     -.7322     -.3656
treathrs     -.7956      .1303    -6.1075      .0000    -1.0528     -.5383

Interactions:

 int_2    bdip        X      mbrp

******************** DIRECT AND INDIRECT EFFECTS *************************

Conditional direct effect(s) of X on Y at values of the moderator(s):
       mbrp     Effect         SE          t          p       LLCI       ULCI
      .0000      .6503      .1124     5.7858      .0000      .4283      .8723
     1.0000     -.1101      .0982    -1.1206      .2641     -.3041      .0839

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
             mbrp     Effect    Boot SE   BootLLCI   BootULCI
crave2      .0000      .3854      .1008      .2003      .6000
crave2     1.0000      .0181      .0656     -.1129      .1449

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** INDEX OF MODERATED MEDIATION ************************

Mediator
            Index   SE(Boot)   BootLLCI   BootULCI
crave2     -.3673      .1120     -.6083     -.1674

When the moderator is dichotomous, this is a test of equality of the
conditional indirect effects in the two groups.

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

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

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

PROCESS output

```
******************** DIRECT AND INDIRECT EFFECTS *************************
```

W $(c'_1 + c'_3W)$ NHSTs and confidence intervals

```
Conditional direct effect(s) of X on Y at values of the moderator(s):
     mbrp     Effect        SE         t         p      LLCI      ULCI
    .0000      .6503     .1124    5.7858     .0000     .4283     .8723
   1.0000     -.1101     .0982   -1.1206     .2641    -.3041     .0839

Conditional indirect effect(s) of X on Y at values of the moderator(s):
```

W $(a_1 + a_3W)b$ Bootstrap confidence intervals

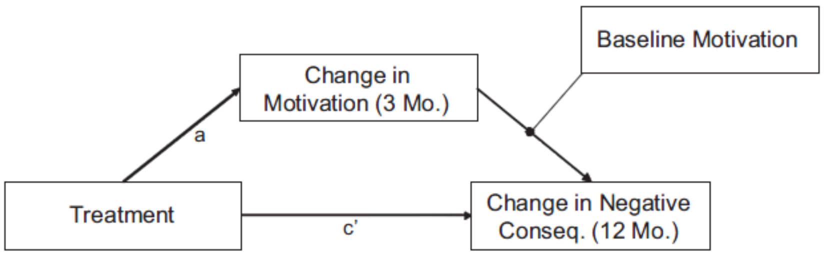
```
Mediator
             mbrp     Effect    Boot SE   BootLLCI   BootULCI
crave2      .0000      .3854      .1008      .2003      .6000
crave2     1.0000      .0181      .0656     -.1129      .1449

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** INDEX OF MODERATED MEDIATION ************************

Mediator
            Index   SE(Boot)   BootLLCI   BootULCI
crave2     -.3673      .1120     -.6083     -.1674

When the moderator is dichotomous, this is a test of equality of the
conditional indirect effects in the two groups.
```

Difference between conditional indirect effects (with bootstrap confidence interval)

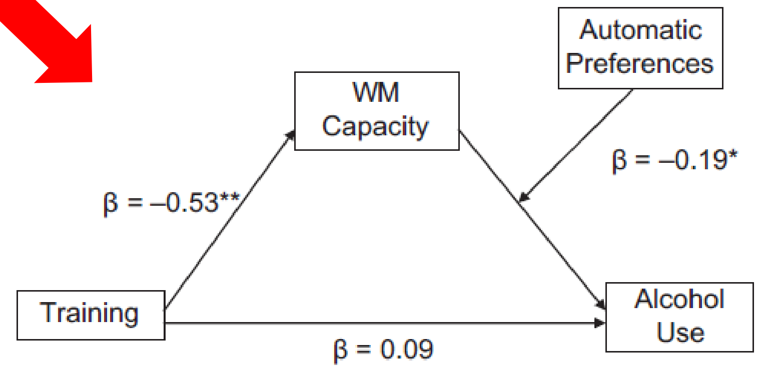
Direct and indirect effects of depression on substance use are positive and statistically different from zero among those given therapy as usual. No direct or indirect effects of depression on substance use among those given MBRP therapy. The indirect effect through craving differs between the two groups---"moderated mediation"

Some other examples

We just examined a "first stage" model. But moderation can occur in the "second stage" of the mechanism as well:



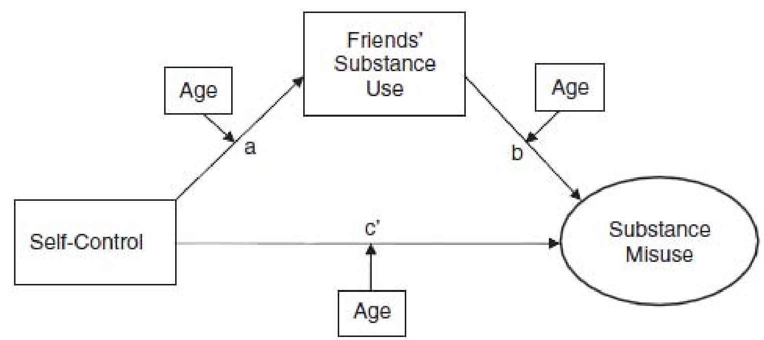
Stein, L. A. R., Minugh, P. A. et al. (2009). Readiness to change as a mediator of the effect of a brief motivational intervention on post-treatment alcohol-related consequences of injured emergency department hazardous drinkers. ***Psychology of Addictive Behaviors**, 23*, 185-195.



Houben, K., Wiers, R. W., & Jansen, A. (2011). Getting a grip on drinking behavior: Training working memory to reduce alcohol abuse. ***Psychological Science**, 22*, 968-975.

....or a variable can moderate both stages of the mechanism.

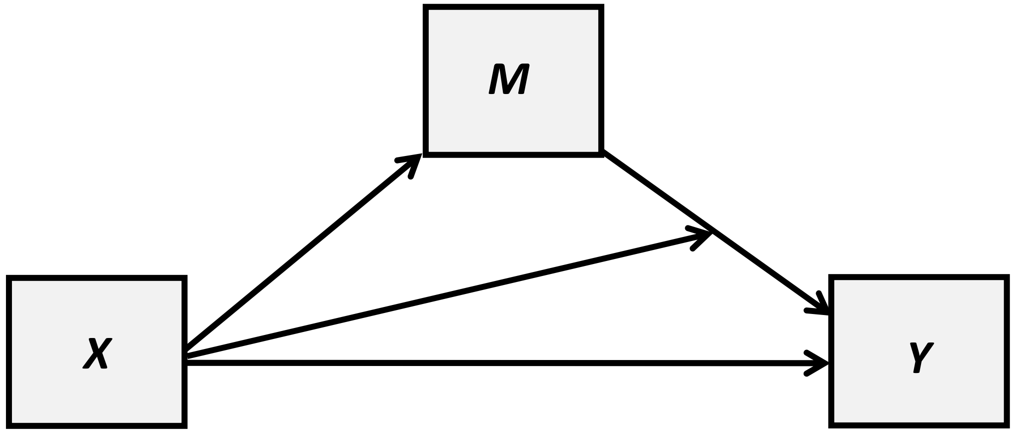
There are many possibilities. The math is different, but the principles are the same.



Malouf, E., Stuewig, J., & Tangney, J. (2012). Self-control and jail inmates' substance misuse post-release: Mediation by friends' substance use and moderation by age. ***Addictive Behaviors**, 37*, 1198-1204.

An intriguing possibility

A causal agent modifying the operation of its own mechanism by which it affects an outcome.



This model is estimated as:

$$\hat{M}_1 = i_1 + aX$$
$$\hat{Y} = i_2 + c'X + b_1 M + b_2 XM$$

or

equivalently

The effect of *X* on *M*

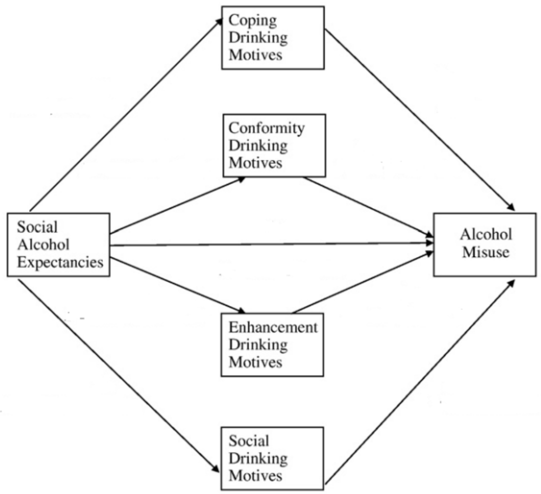
$$\hat{M}_1 = i_1 + aX$$

The effect of *M* on *Y*

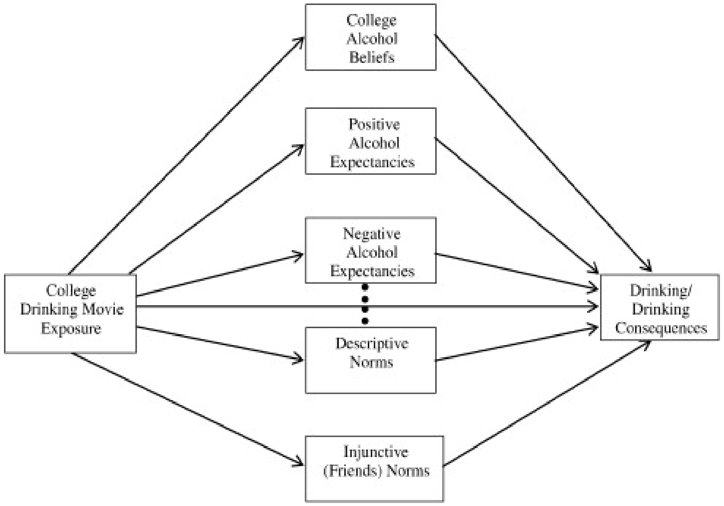
$$\hat{Y} = i_2 + c'X + \overline{(b_1 + b_2 X)}M$$

The effect of *X* on *M* is just "*a*", but the the effect of *M* on *Y* depends on *X*: $b_1 + b_2X$. The indirect effect of *X* is the product of these effects: $a(b_1 + b_2X) = ab_1 + ab_2X$ **and so depends on *X*.** **This makes sense to do only if *X* is not dichotomous**.

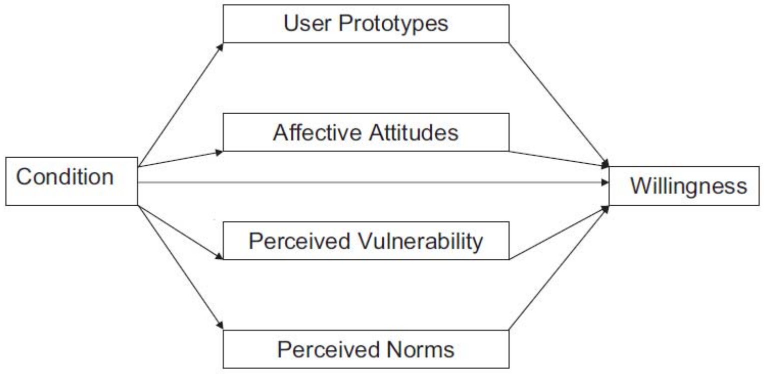
Multiple mechanisms modeled simultaneously



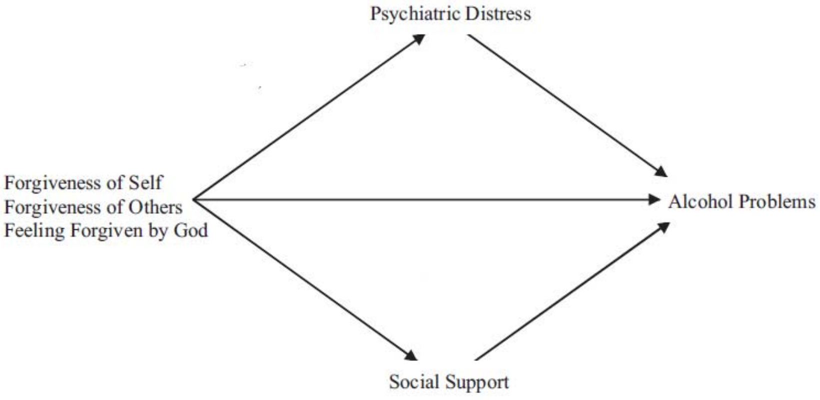
Kong, G., Bergman, A. (2010). A motivational model of alcohol misuse in emerging adulthood. ***Addictive Behaviors**, 35, 855-860.*



Osberg, T. M., Billingsley,K., Eggert,M.,& Insana, M. (2012). From *Animal House* to *Old School*: A multiple mediation analysis of the association between college drinking movie exposure and freshman drinking and its consequences*.* ***Addictive Behaviors**, 37*, 922-930.



Litt, D. M., & Stock, M. L. (2011). Adolescent alcohol-related risk cognitions: The roles of social norms and social networking sites. ***Psychology of Addictive Behaviors**, 25*, 708-713.



Webb,J. R., Robinson, E. A. R., & Brower, K. J. (2013). Mental health, not social support, mediates the forgiveness-alcohol outcome relationships. ***Psychology of Addictive Behaviors***, 25, 462-473.

Why estimate such a model?

- Many causal effects probably operate through multiple mechanisms simultaneously. Better to estimate a model consistent with such real-world complexities.

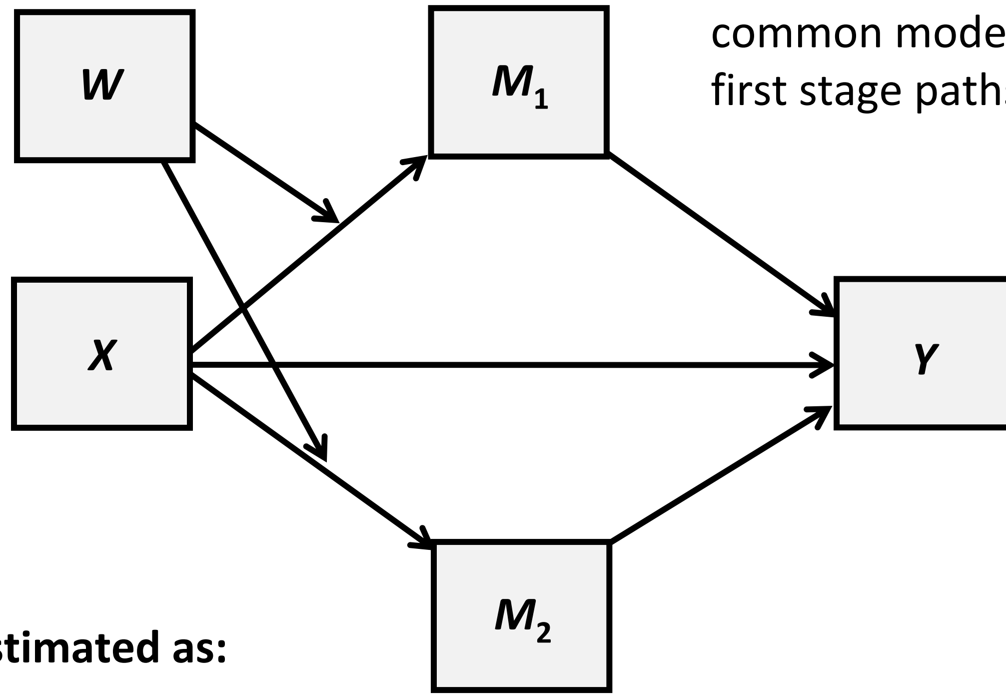
- If your proposed mediator is correlated with the "real" mediator but not caused by the independent variable, a model with only your proposed mediator in it will be a misspecification and will potentially misattribute the process to your proposed mediator rather than the real mediator—"epiphenomenality."

- Different theories may postulate different mediators as mechanisms. Including them all in a model simultaneously allows for a formal statistical comparison of indirect effects representing different theoretical mechanisms.

- When combined with moderation, allows for the modeling of different mechanisms for different people defined by different values of a moderator.

An interesting extension

Mechanisms might be different for different types of people. For some types, mechanism 1 may be dominant, whereas for other types, mechanism 2 may dominate. For example:



A conditional process model with a common moderator of both of the first stage paths of the mechanism.

This model is estimated as:

$$\hat{M}_1 = i_1 + a_{11}X + a_{12}W + a_{13}XW$$
$$\hat{M}_2 = i_2 + a_{21}X + a_{22}W + a_{23}XW$$
$$\hat{Y} = i_3 + c'X + b_1M_1 + b_2M_2$$

or

equivalently

$$\hat{M}_1 = i_1 + (a_{11} + a_{13}W)X + a_{12}W$$
$$\hat{M}_2 = i_2 + (a_{21} + a_{23}W)X + a_{22}W$$
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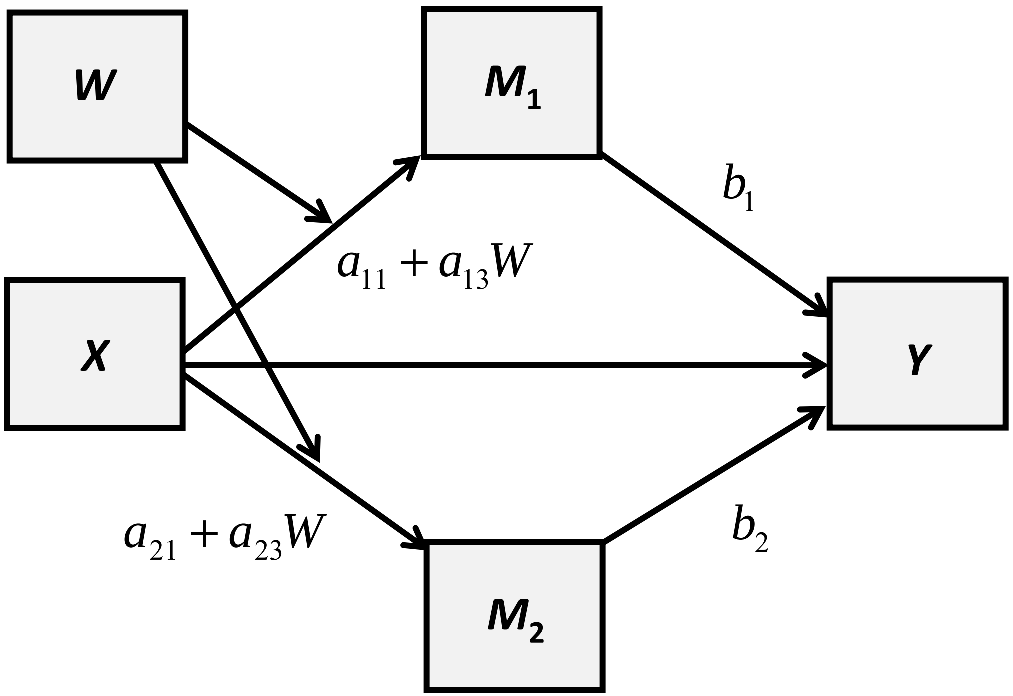

$$\hat{M}_1 = i_1 + (a_{11} + a_{13}W)X + a_{12}W$$
$$\hat{M}_2 = i_2 + (a_{21} + a_{23}W)X + a_{22}W$$
$$\hat{Y} = i_3 + c'X + b_1M_1 + b_2M_2$$

Indirect effect of X on Y through M_1 depends on W:

$$\omega_1 = (a_{11} + a_{13}W)b_1$$
$$= a_{11}b_1 + a_{13}b_1W$$

Indirect effect of X on Y through M_2 depends on W:

$$\omega_2 = (a_{21} + a_{23}W)b_2$$
$$= a_{21}b_2 + a_{23}b_2W$$

A conditional process model with a common moderator of both of the first stage paths of the mechanism.

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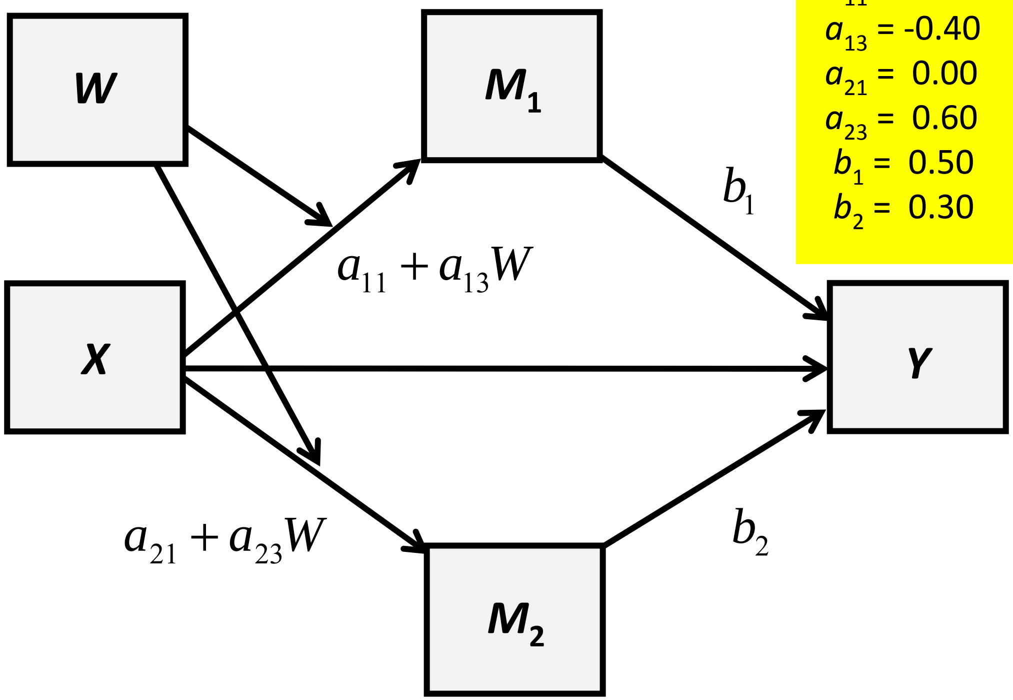
Mechanisms might be different for different types of people. For some types, mechanism 1 may be dominant, whereas for other types, mechanism 2 may dominate.



a_{11} = 0.40
a_{13} = -0.40
a_{21} = 0.00
a_{23} = 0.60
b_1 = 0.50
b_2 = 0.30

$$\hat{M}_1 = i_1 + (a_{11} + a_{13}W)X + a_{12}W$$

$$\hat{M}_2 = i_2 + (a_{21} + a_{23}W)X + a_{22}W$$

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A conditional process model with a common moderator of both of the first stage paths of the mechanism.

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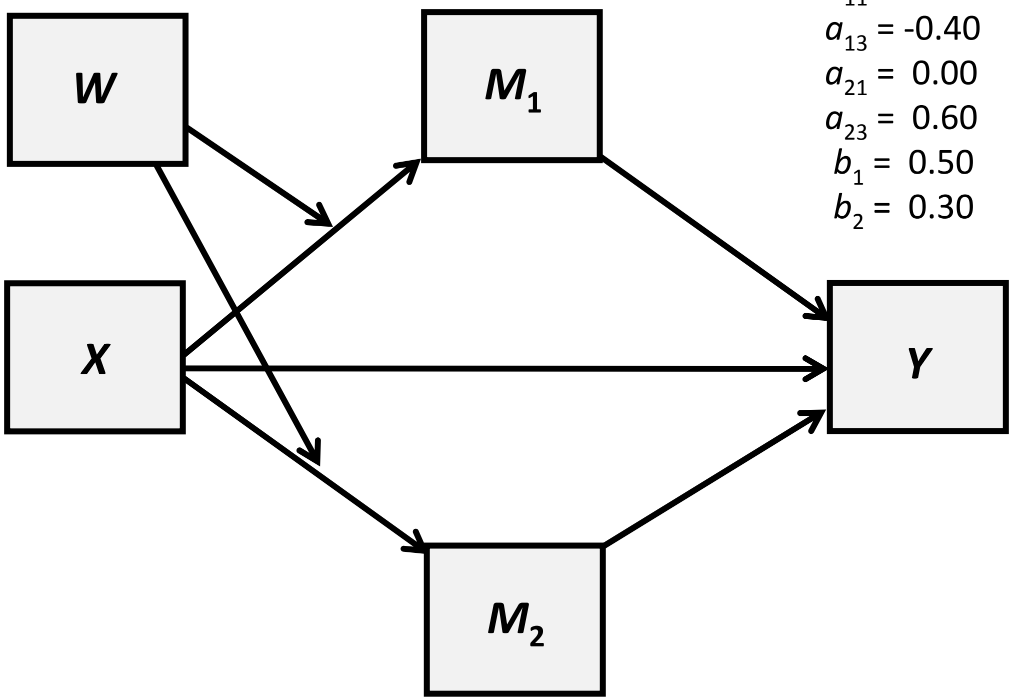

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Indirect effect of X on Y through M_1 depends on W:

$$\omega_1 = (a_{11} + a_{13}W)b_1$$
$$\omega_1 = (0.40 - 0.40W)0.50$$
$$\omega_1 = 0.20 - 0.20W$$

Indirect effect of X on Y through M_2 depends on W:

$$\omega_2 = (a_{21} + a_{23}W)b_2$$
$$\omega_2 = (0.00 + 0.60W)0.30$$
$$\omega_2 = 0.00 + 0.18W$$

A conditional process model with a common moderator of both of the first stage paths of the mechanism.

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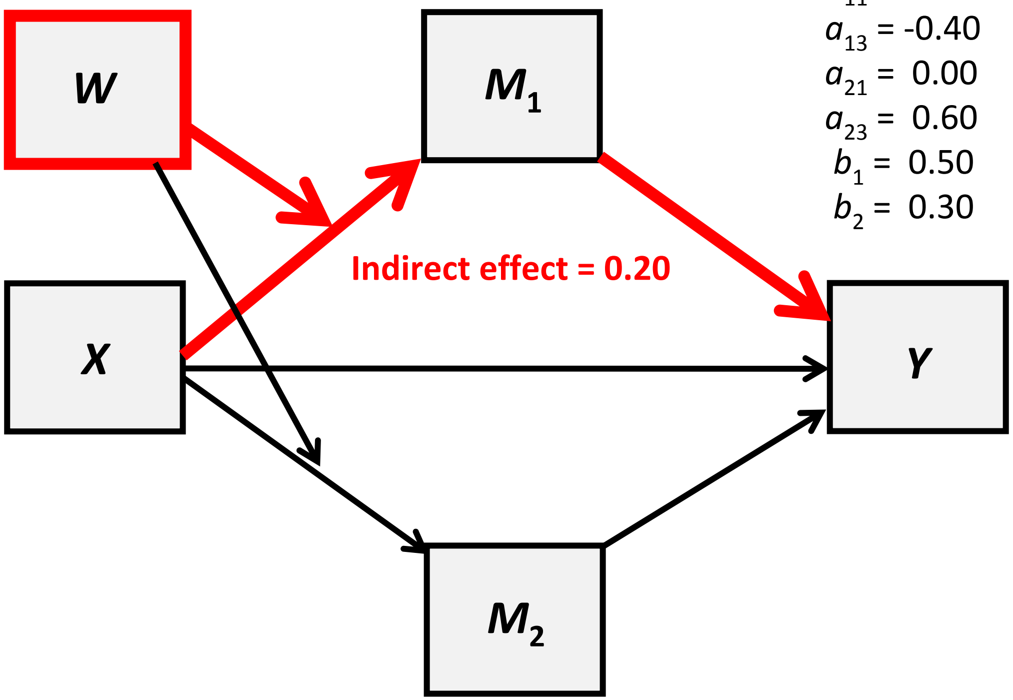

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$$\hat{M}_2 = i_2 + (0.00 + 0.60W)X + a_{22}W$$
$$\hat{Y} = i_3 + c'X + 0.50M_1 + 0.30M_2$$

Indirect effect of X on Y through M_1 when $W = 0$:

$$\omega_1 = (a_{11} + a_{13}W)b_1$$
$$\omega_1 = (0.40 - 0.40 \times 0)0.50$$
$$\omega_1 = 0.20 - 0.20 \times 0 = 0.20$$

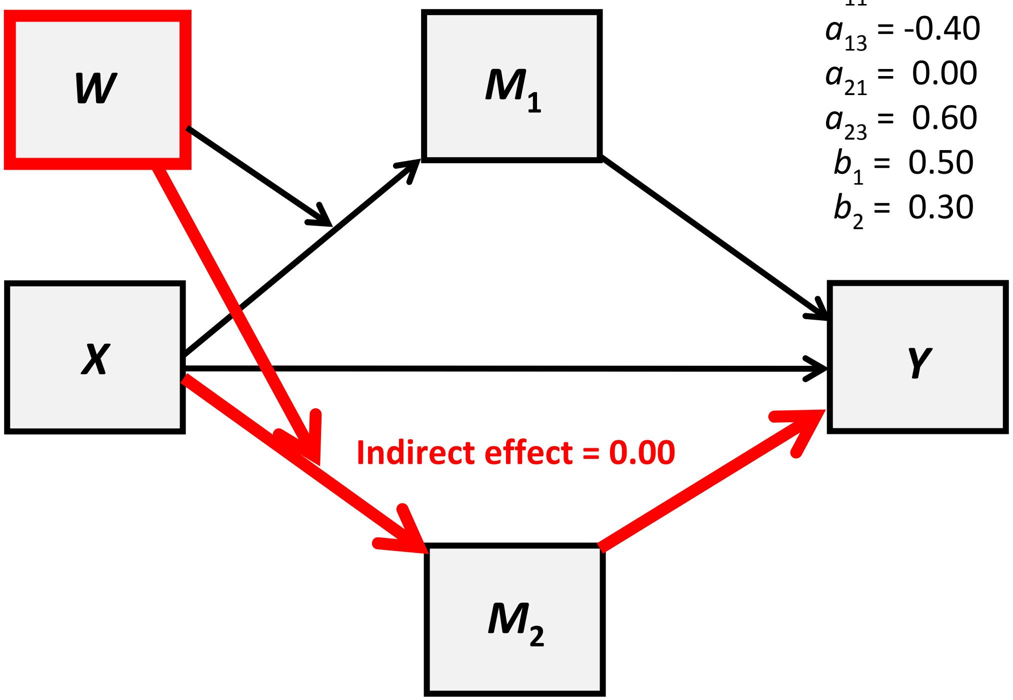
Indirect effect of X on Y through M_2 when $W = 0$:

$$\omega_2 = (a_{21} + a_{23}W)b_2$$
$$\omega_2 = (0.00 + 0.60W)0.30$$
$$\omega_2 = 0.00 + 0.18W$$

For people of **type A** (e.g., $W = 0$) X affects Y through M_1 but not through M_2.

An interesting extension

Mechanisms might be different for different types of people. For some types, mechanism 1 may be dominant, whereas for other types, mechanism 2 may dominate.



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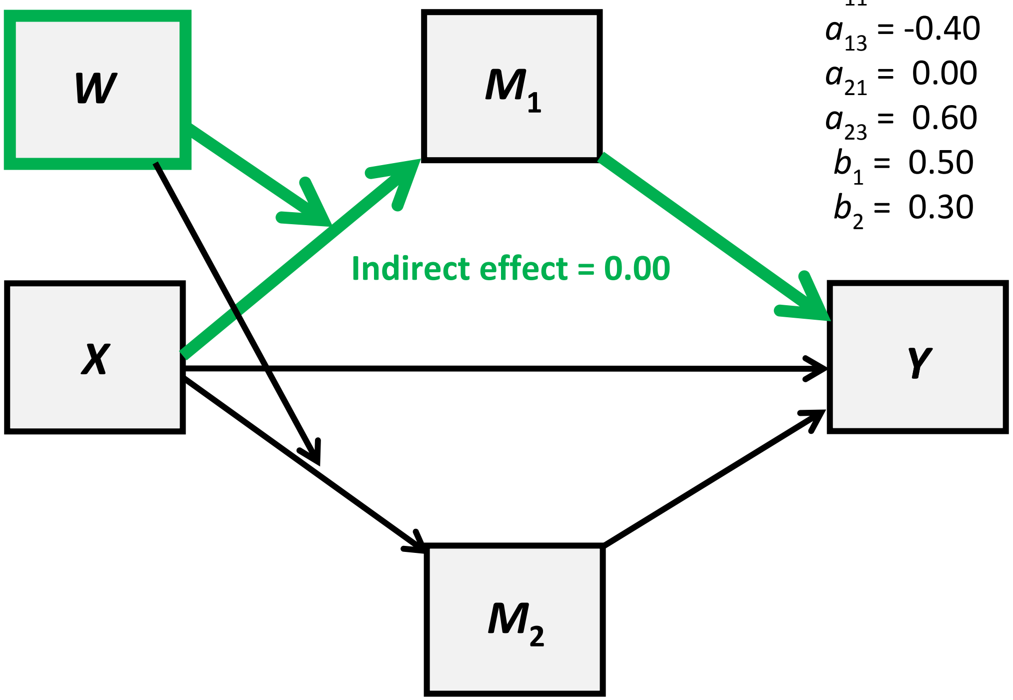

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$$\hat{M}_2 = i_2 + (0.00 + 0.60W)X + a_{22}W$$
$$\hat{Y} = i_3 + c'X + 0.50M_1 + 0.30M_2$$

Indirect effect of X on Y through M_1 when **W = 1**:

$$\omega_1 = (a_{11} + a_{13}W)b_1$$
$$\omega_1 = (0.40 - 0.40 \times 1)0.50$$
$$\omega_1 = 0.20 - 0.20 \times 1 = 0.00$$

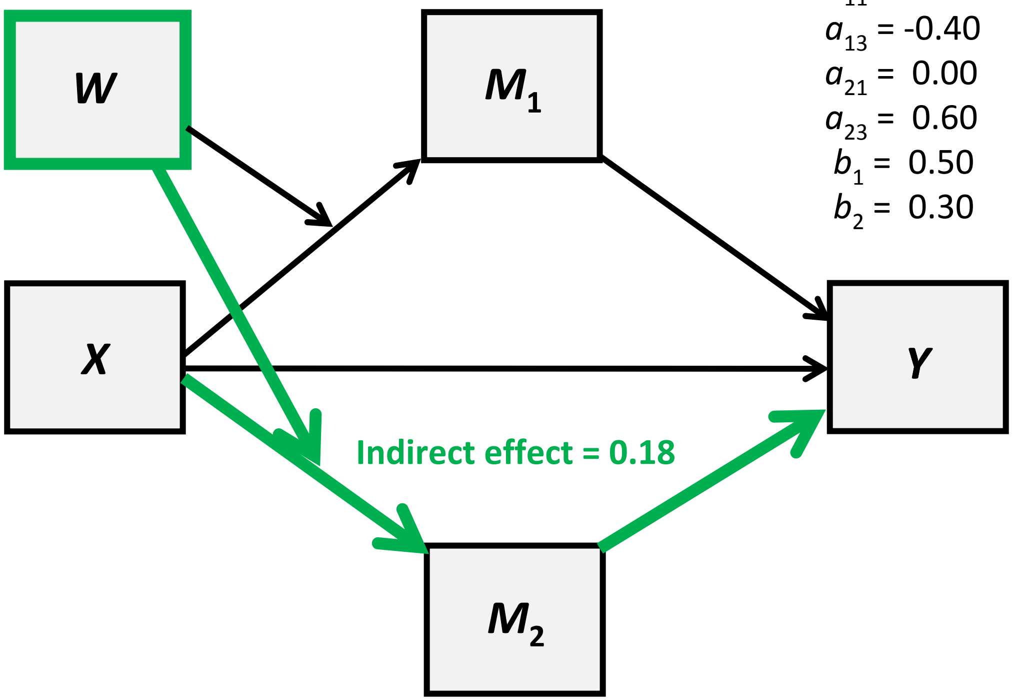
Indirect effect of X on Y through M_2 when W = 1:

$$\omega_2 = (a_{21} + a_{23}W)b_2$$
$$\omega_2 = (0.00 + 0.60W)0.30$$
$$\omega_2 = 0.00 + 0.18W$$

For people of **type B** (e.g., ***W* = 1**) X affects Y through M_2 but not through M_1.

An interesting extension

Mechanisms might be different for different types of people. For some types, mechanism 1 may be dominant, whereas for other types, mechanism 2 may dominate.



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$$\omega_1 = 0.20 - 0.20 \times 1 = 0.00$$

Indirect effect of X on Y through M_2 when **W = 1**:

$$\omega_2 = (a_{21} + a_{23}W)b_2$$
$$\omega_2 = (0.00 + 0.60 \times 1)0.30$$
$$\omega_2 = 0.00 + 0.18 \times 1 = 0.18$$

For people of **type B** (e.g., **W = 1**) X affects Y through M_2 but not through M_1.

In closing…

These are slides at **www.afhayes.com/public/mobc.pdf**

- All causal effects operate through some kind of mechanism---a causal chain of events. But all effects are contingent on something.
- Mechanisms that are contingent can be modeled if we understand or can at least hypothesize something about those contingencies.
- Quantifications of mechanisms (indirect effects) can be modeled as functions of other variables (moderators).
- Simple combinations of moderation and mediation can be put together to yield complex models that are yet fairly simple to estimate and interpret.
- Statistical tools exist to make the modeling easy, and people are beginning to do this in earnest in many areas of research, including substance use.
- Learning resources are scattered throughout the methodology journals. The advice they offer is often inconsistent, sometimes dated.

Some places to go for help

www.afhayes.com

Andrew F. Hayes, Ph.D.

- Home
- My C.V.
- Teaching and Speaking
- Mechanisms and Contingencies Lab
- Introduction to Mediation, Moderation, and Conditional Process Analysis
- SPSS, SAS, and Mplus Macros and Code
- Mediation and Moderation Analysis Workshops
- Video
- Blog
- Tweets

STATISTICAL HORIZONS

Now registering for my July 2014 introductory moderation and mediation analysis course.

Andrew F. Hayes, Ph.D.
Department of Psychology
The Ohio State University
Columbus, OH 43210, U.S.A.
hayes.338@osu.edu

I am a Professor of Quantitative Psychology at The Ohio State University. My research focuses on linear models, with an emphasis on resampling methods of inference. Specific areas of investigation and writing include statistical approaches to assessing mediation and moderation. I hold a Ph.D. in Psychology from Cornell University (1996) and a B.A. in Psychology from San Jose State University (1991).

My methodology work is published in such locations as *Psychological Methods, Multivariate Behavioral Research, Behavior Research Methods, Psychological Science, British Journal of Mathematical and Statistical Psychology, Journal of Educational and Behavioral Statistics, and the Journal of Statistical Computation and Simulation.* In May 2013 I released my third book, "Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach" through The Guilford Press.

I teach various classes on data analysis at the graduate level. Courses include Introductory Statistics, Multiple Regression, Moderation and Mediation Analysis, Structural Equation Modeling, and various miscellaneous special topics. I regularly conduct workshops on moderation and mediation analysis at institutions throughout the world. I also teach for Statistical Horizons.

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Some places to go for help

www.statisticalhorizons.com

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Mediation and Moderation

A 5-Day Seminar Taught by Andrew Hayes, Ph.D.

Read reviews of this course

This seminar focuses on two topics in causal analysis that are closely related and often confused. Suppose we have three variables, X, M and Y. We say that M is a **mediator** of the effect of X on Y if X carries its influence on Y at least partly by influencing M, which then influences Y. This is also known as an **indirect effect** of X on Y through M. On the other hand, we say that M **moderates** the effect of X on Y if that effect varies in size, sign, or strength as a function of M. This is also known as **interaction**.

Although these concepts are fairly simple, the statistical issues that arise in estimating and testing mediation and moderation effects turn out to be rather complex and subtle. **Andrew Hayes** has been among the leading recent contributors to the literature on these methods. He has developed powerful new methods for estimating mediation and moderation effects and special software tools that can be used with SAS or SPSS.

In this seminar, you will learn about the underlying principles and the practical applications of these methods. The seminar is divided roughly into three parts:

1. Partitioning effects into direct and indirect components, and how to quantify and test hypotheses about indirect effects.

2. Estimating, testing, probing, and visualizing interactions in linear models.

3. Integrating moderation and mediation by discussing how to estimate conditional indirect effects, determine whether an indirect effect is moderated (moderated mediation) and whether moderated effects are mediated (mediated moderation).

Computer applications will focus on the use of OLS regression and computational modeling tools for SPSS and SAS (including the PROCESS add on developed by Hayes). When appropriate, some Mplus code will be provided for those interested, but structural equation modeling and Mplus will

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SEMINAR
INFORMATION

Monday July 14, 2014 9:00 AM -
Friday July 18, 2014 5:00 PM (Eastern Time)

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Philadelphia, Pennsylvania 19103
United States
View Map

CONTACT
INFORMATION

Phone: 610-642-1941
Fax: 419-818-1220
Email: info@statisticalhorizons.com

PAYMENT
INSTRUCTIONS

The fee of $1695 includes all course materials. The early registration fee of $1495 is available until June 16.

PayPal and all major credit cards are accepted.

Our Tax ID number is 26-4576270.

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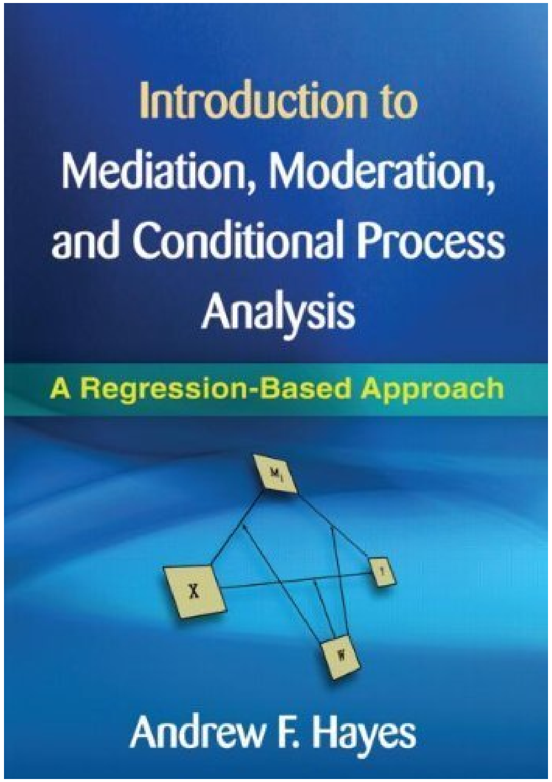
Some places to go for help



Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression based approach.* New York: The Guilford Press.

Hayes, A. F., & Preacher, K. J. (2013). Conditional process modeling: Using SEM to examine contingent causal processes. In G. R. Hancock and R. O. Mueller (Eds.) *Structural equation modeling: A second course* (2^{nd} Ed). Information Age Publishing.