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PSYCH 224
Research Designs
For Health Service Programs
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LAB 3

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What is Mediation?

A mediation model hypothesizes that the independent variable (X) influences the mediator variable (M), which in turn influences the dependent variable (Y). In other words, X leads to M leads to Y. Thus, the mediator variable serves to clarify the nature of the relationship between the independent and dependent variables.

X → M → Y

Mediation analysis also makes all of the standard assumptions of the general linear model (i.e., linearity, normality, homogeneity of error variance, and independence of errors).

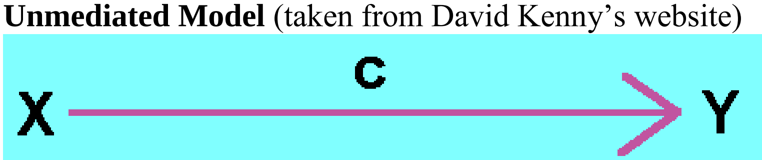
3 main types of mediation:

1. *Indirect effect:* predicts no direct effect from X to Y. However, X has a direct effect on the mediator, and the mediator has a direct effect on Y. Thus, X is said to have an indirect effect on Y. This hypothesis can only be supported if the direct effect of X to Y is insignificant prior to testing for indirect effects.

2. *Partial mediation:* predicts significant direct and indirect effects from X to Y. Thus, the unmediated relationship is significant as well as the X to mediator and mediator to Y relationships.

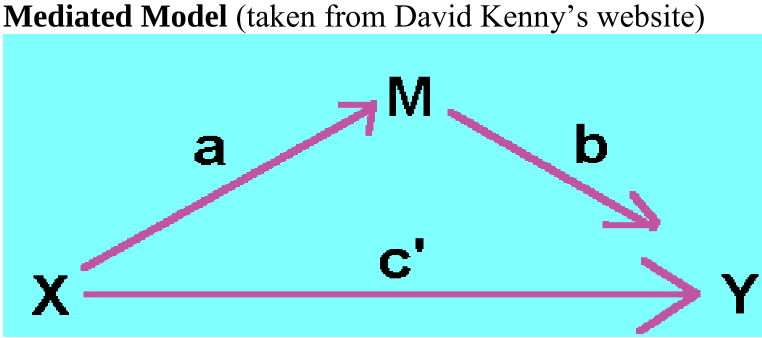
3. *Full mediation:* predicts that the direct effect of X to Y will be significant only if the mediator is absent. When the mediator is present, this direct effect becomes insignificant, while the indirect effect is significant. Lastly, if the X to mediator and/or the mediator to Y relationships are insignificant, no mediation is taking place.

Unmediated Model (taken from David Kenny's website)



Path c in the above model is called the total effect. The effect of X on Y may be mediated by variable M, and the variable X may still affect Y.

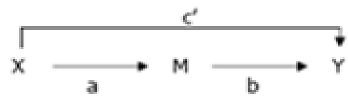
Mediated Model (taken from David Kenny's website)



Path c' in the above model is called the direct effect. Complete mediation is the case in which variable X no longer affects Y after M has been controlled and so path c' is zero. Partial mediation is the case in which the path from X to Y is reduced in absolute size but is still different from zero when the mediator is introduced.

<u>Baron and Kenny's Four Steps:</u>

Baron and Kenny (1986) proposed a four-step approach in which several regression analyses are conducted and significance of the coefficients is examined at each step. Take a look at the diagram below to follow the description (note that c' could also be called a direct effect.



	Analysis	*Visual Depiction*
Step 1	Conduct a simple regression analysis with X predicting Y to test for path *c* alone, $Y = B_0 + B_1X + e$	$X \xrightarrow{c} Y$
Step 2	Conduct a simple regression analysis with X predicting M to test for path *a*, $M = B_0 + B_1X + e$.	$X \xrightarrow{a} M$
Step 3	Conduct a simple regression analysis with M predicting Y to test the significance of path *b* alone, $Y = B_0 + B_1M + e$.	$M \xrightarrow{b} Y$
Step 4	Conduct a multiple regression analysis with X and M predicting Y, $Y = B_0 + B_1X + B_2M + e$	$X \xrightarrow{c'} Y$, $M \xrightarrow{b} Y$

What these steps mean:

Step 1: Run a simple regression analysis with a single predictor (X) and the outcome variable Y. This will establish that there is an association between X and Y that can be mediated

Step 2: Step 2: Run a simple regression analysis with a single predictor (X) and M as the outcome variable. This will establish that there is an association between X and M

Step 3: Show that the mediator affects the outcome variable. Use Y as the criterion variable in a regression equation and X and M as predictors (estimate and test path b). It is not sufficient just to correlate the mediator with the outcome because the mediator and the outcome may be correlated because they are both caused by the causal variable X. Thus, the causal variable must be controlled in establishing the effect of the mediator on the outcome.

Step 4: To establish that M completely mediates the X-Y relationship, the effect of X on Y controlling for M (path c') should be zero. The effects in both Steps 3 and 4 are estimated in the same equation.

If all four of these steps are met, then the data are consistent with the hypothesis that variable M completely mediates the X-Y relationship, and if the first three steps are met but the Step 4 is not, then partial mediation is indicated.

How to do this in SPSS:

Our example:

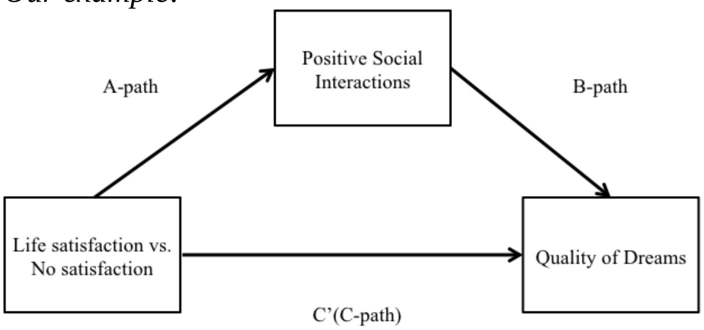


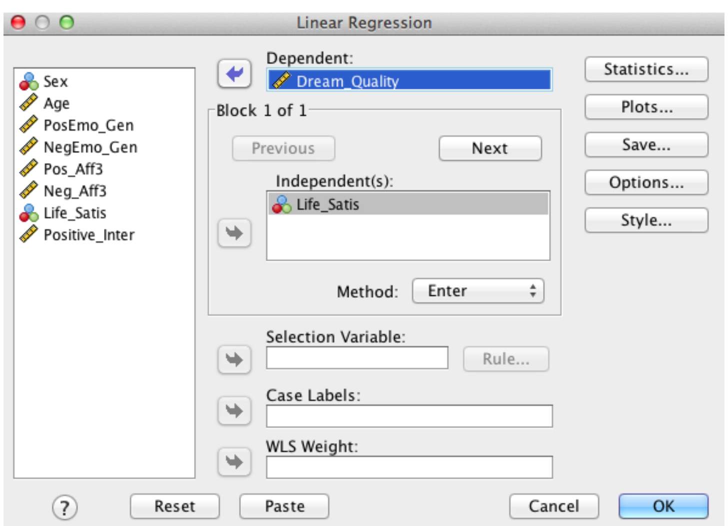
Figure 1. Indirect effect of Life satisfaction on Quality of Dreams through Positive Social Interactions.

Note: $*p < .05$, $**\ p < .01$, $***p < .001$

The model we will be looking at today is the indirect effect of life satisfaction on quality of dreams through positive social interactions. Participants are randomly assigned to one of two conditions (life satisfaction vs. no satisfaction) based on self-report. Then they report how many positive social interactions they had that day. Then later that night they report how well they slept.

Step 1 (Path c): Analyze → Regression → Linear

Drag Life_Satis into the Independent Box and Dream_Quality into the Dependent Box



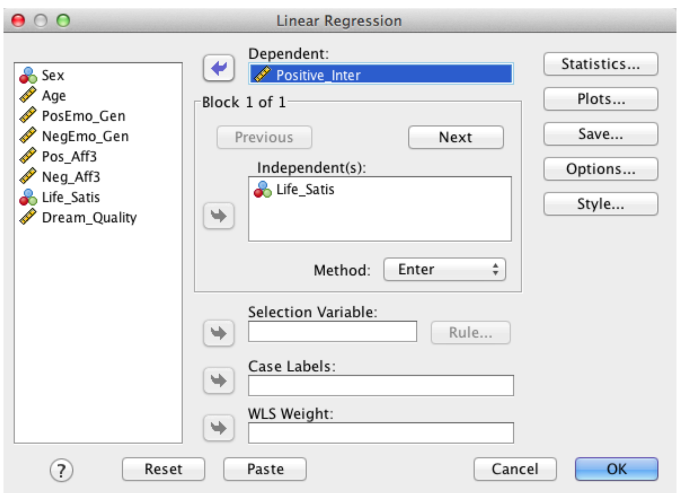
Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	3.513	.051		69.425	.000
Life_Satis	.326	.073	.299	4.495	.000

a. Dependent Variable: Dream_Quality

*Significant!

Step 2 (Path a): Analyze→Regression→Linear
Keep Life_Satis in the Independent Box, remove Dream_Quality and drag Positive_Inter into the Dependent Box.



Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	1.102	.038		28.721	.000
Life_Satis	.960	.055	.772	17.427	.000

a. Dependent Variable: Positive_Inter

*Significant!

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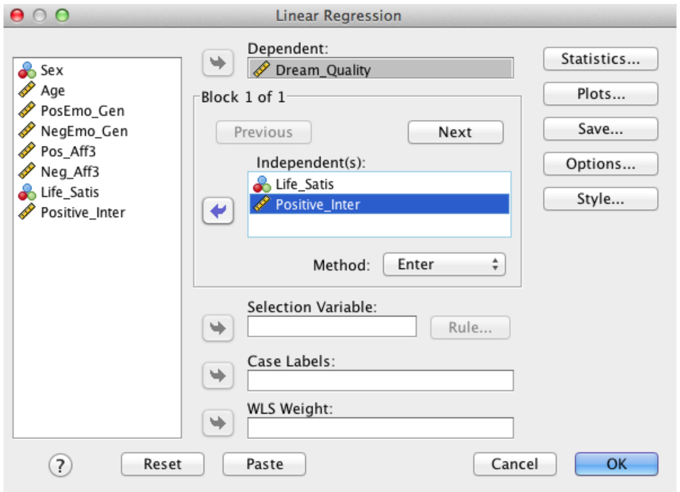
Step 3 (Path b): Analyze→Regression→Linear
Drag Dream_Quality into the Dependent Box. Drag Positive_Inter and Life_Satis in the Independent Box



Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	3.299	.112		29.391	.000
Life_Satis	.140	.113	.128	1.234	.219
Positive_Inter	.194	.091	.221	2.135	.034

a. Dependent Variable: Dream_Quality

*Positive social interaction is positively associated with dream quality ($p<.05$)!

Step 4 (Path c'): The direct effect of life satisfaction on dream quality has become non-significant ($p=.21$)

Because both the a-path and b-path were significant, mediation analyses will be tested using the sobel test and bootstrapping method.

<u>The Indirect Effect</u>

The amount of mediation is called the indirect effect.
Note that the total effect = direct effect + indirect effect, or using symbols: $c = c' + ab$
Note also that the indirect effect is: $ab = c - c'$.
In contemporary mediational analyses, the indirect effect or ab is the measure of the amount of mediation. Below are two described tests of the indirect effect or ab.

Sobel Test

A test, first proposed by Sobel (1982), was initially often used. The Sobel test assesses whether a mediation effect is significant. The Sobel test can be conducted using the standardized or unstandardized coefficients. Care must be taken to use the appropriate standard errors if standardized coefficients are used.

Sobel test can be done here by plugging in the numbers for a, b, S^a and S^b: http://quantpsy.org/sobel/sobel.htm

To conduct the Sobel test

Details can be found in Baron and Kenny (1986), Sobel (1982), Goodman (1960), and MacKinnon, Warsi, and Dwyer (1995). Insert the a, b, s_a, and s_b into the cells below and this program will calculate the critical ratio as a test of whether the indirect effect of the IV on the DV via the mediator is significantly different from zero.

Input:			Test statistic:	Std. Error:	p-value:
a	.96	Sobel test:	2.0984642	0.08692071	0.03586416
b	.19	Aroian test:	2.09565761	0.08703712	0.03611257
s_a	.05	Goodman test:	2.10128209	0.08680415	0.03561621
s_b	.09	Reset all	Calculate		

a = raw (unstandardized) regression coefficient for the association between IV and mediator.
S^a = standard error of a.
b = raw coefficient for the association between the mediator and the DV (when the IV is also a predictor of the DV).
S^b = standard error of b.

The Sobel test is very conservative (MacKinnon, Warsi, & Dwyer, 1995), and so it has very low power. Bootstrapping has replaced the Sobel test (According to Kenny's website). The Sobel test works well only in large samples and it is recommended to use this test only if the user has no access to raw data (according to Preacher's website).

Bootstrapping Method

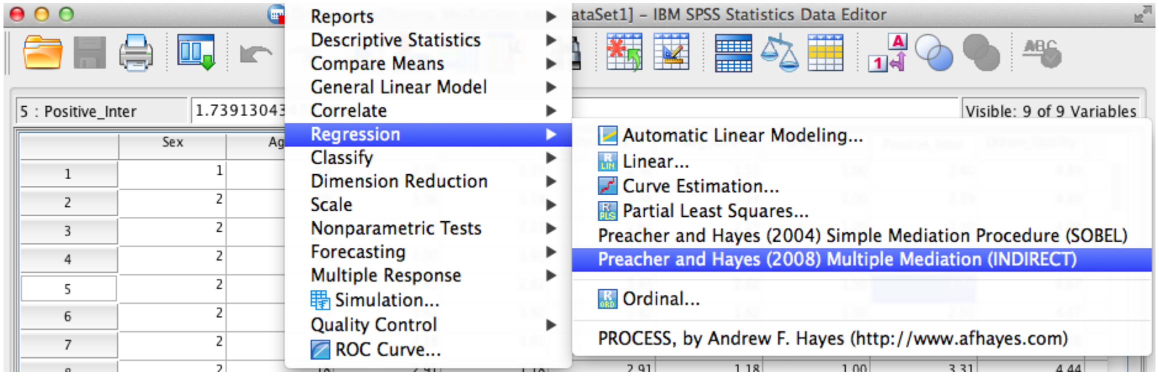
Bootstrapping is an increasingly popular method of testing the indirect effect. The indirect effect is the amount of mediation. Bootstrapping is a non-parametric method based on resampling with replacement, which is done many times, e.g., 5000 times. From each of these samples the indirect effect is computed and a sampling distribution can be empirically generated. Very typically a confidence interval is computed and it is checked to determine if zero is in the interval. *If zero is not in the interval, then the researcher can be confident that the indirect effect is different from zero.*

Mediation Example

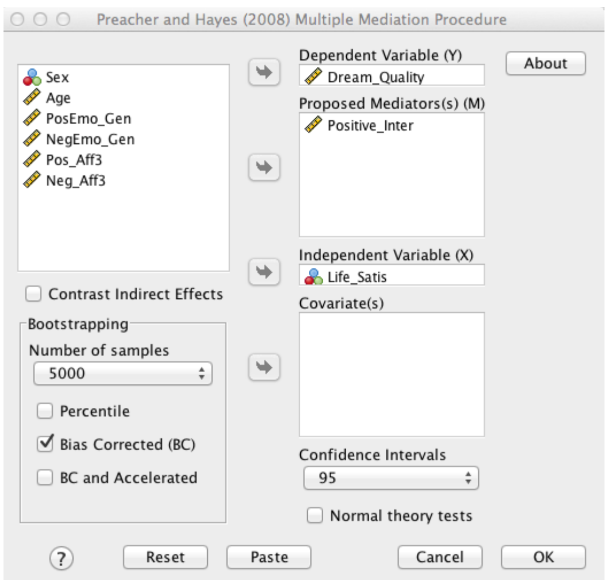
First, you must download Preacher and Hayes INDIRECT from Hayes' website: http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html

How to do run in SPSS:

1) Analysis → Regression → Preacher and Hayes Multiple Mediator INDIRECT



2) Drag Life_Satis into the Independent Variable Box, drag Positive_Inter into the Proposed Mediator Box, and drag Dream_Quality into the Dependent Variable Box. Under Bootstrapping, select 5,000 for the number of samples.



3) Click OK

4) Examine Output

```
Dependent, Independent, and Proposed Mediator Variables:
DV =   Dream_Qu
IV =   Life_Sat
MEDS = Positive

Sample size
        208

IV to Mediators (a paths)
             Coeff        se         t          p
Positive     .9599     .0551   17.4271      .0000

Direct Effects of Mediators on DV (b paths)
             Coeff        se         t          p
Positive     .1944     .0911    2.1351      .0339

Total Effect of IV on DV (c path)
             Coeff        se         t          p
Life_Sat     .3264     .0726    4.4949      .0000

Direct Effect of IV on DV (c' path)
             Coeff        se         t          p
Life_Sat     .1398     .1133    1.2340      .2186

Model Summary for DV Model
      R-sq  Adj R-sq         F       df1       df2          p
     .1091     .1004   12.5561    2.0000  205.0000      .0000

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

           BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)
              Data      Boot      Bias        SE
TOTAL        .1866     .1855    -.0012     .0780
Positive     .1866     .1855    -.0012     .0780

Bias Corrected Confidence Intervals
             Lower     Upper
TOTAL        .0283     .3374
Positive     .0283     .3374

*****************************************************************
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IV to Mediators (a paths)

	Coeff	se	t	p
Positive	**.9599**	.0551	17.4271	**.0000**

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
Positive	**.1944**	.0911	2.1351	**.0339**

Total Effect of IV on DV (c path)

	Coeff	se	t	p
Life_Sat	**.3264**	.0726	4.4949	**.0000**

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Life_Sat	**.1398**	.1133	1.2340	**.2186**

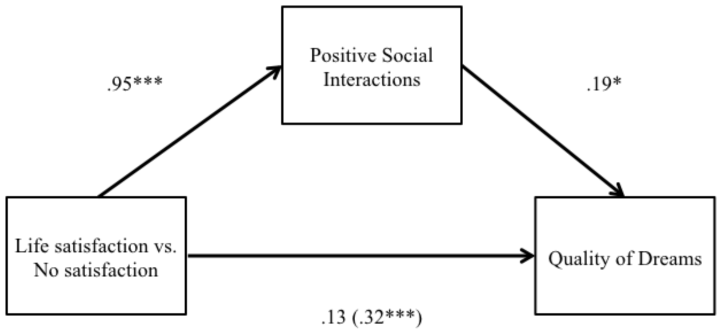

Figure 1. Indirect effect of Life satisfaction on Quality of Dreams through Positive Social Interactions.

Note: **p* < .05, ** *p* < .01, ****p* < .001

What do these numbers mean??
For the relationship between life satisfaction and positive social interactions, the coefficient suggests that one unit increase of life satisfaction, results in a .95 increase in positive social interaction. For the b Path, a one unit increase in positive social interaction results in a .19 increase in quality of dreams. The coefficient for the c Path (X→Y without M) is very significant (B=.32***). The c' Path is no longer significant (B=.13). Putting in this mediator reduces the significance for the c Path, which suggests that this is a good mediator!!

Is the Indirect Effect Significant?
We have to look at the confidence intervals in our output to determine that. If the value 0 is included in the confidence intervals, the indirect effect is not significant.

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0283	.3374
Positive	.0283	.3374

*0 is not included so therefore the indirect effect IS significant.

<u>How to write out this output in APA style:</u>

Results

Multiple regression analyses were conducted to assess each component of the proposed mediation model. First, it was found that life satisfaction was positively associated with dream quality (B = .32, t (206) = 4.49, p = .001). It was also found that life satisfaction (as opposed to the no satisfaction) was positively related to positive social interactions (B = .95, t (206) = 17.42, p = .001). Lastly, results indicated that the mediator, positive social interactions, was positively associated with dream quality (B = .19, t (206) = 2.13, p = .03). Because both the a-path and b-path were significant, mediation analyses were tested using the bootstrapping method with bias-corrected confidence estimates (MacKinnon, Lockwood, & Williams, 2004; Preacher & Hayes, 2004). In the present study, the 95% confidence interval of the indirect effects was obtained with 5000 bootstrap resamples (Preacher & Hayes, 2008). Results of the mediation analysis confirmed the mediating role of positive social interactions in the relation between life satisfaction and dream quality (B = .18; CI = .02 to .33). In addition, results indicated that the direct effect of life satisfaction on dream quality became non-significant (B = .13, t (206) = 1.23, p = .21) when controlling for positive social interactions, thus suggesting full mediation.