## R Workshop: Mediation and Moderation

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Jsing Moderation and Mediation Usings Hayes PROCESS Macro (for R)  A Moderation Example Using Hayes PROCESS Macro
<pre>library(mediation) library(psych) library(tidyverse)  # Created Toy Data Set # Variance Covariance sigma &lt;- rbind(c(1,-0.4,-0.3), c(-0.4,1, 0.7), c(-0.3,0.7,1))</pre>
# Variance Covariance sigma <- rbind(c(1,-0.4,-0.3), c(-0.4,1, 0.7), c(-0.3,0.7,1))
<pre>mu &lt;- c(7, 50, 7) # Generate the Multivariate Normal Distribution df &lt;- as.data.frame(mvrnorm(n=100, mu=mu, Sigma=sigma)) df &lt;- round(df,0) colnames(df) &lt;- c("mediator1","outcome","predictor") df\$condition &lt;- rep(1:2,50)</pre>

#### Running a Moderation Analysis in R

```
moderation <- lm(outcome ~ condition*predictor, data = df)
summary(moderation)</pre>
1
```

- ① Create a mediation object using the lm() function. The condition\*predictor syntax gets you both the main effects of condition and predictor as well as the interaction effect between the two
- (2) Show a summary of the moderation using the summary() function.

#### Call:

```
lm(formula = outcome ~ condition * predictor, data = df)
```

#### Residuals:

```
Min 1Q Median 3Q Max -1.79555 -0.56073 -0.05061 0.55043 1.71457
```

#### Coefficients:

```
Estimate Std. Error t value Pr(>|t|)

(Intercept) 44.85018 1.68125 26.677 < 2e-16 ***

condition -0.01414 1.06533 -0.013 0.98943

predictor 0.76026 0.23452 3.242 0.00163 **

condition:predictor -0.01533 0.14964 -0.102 0.91864

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.8027 on 96 degrees of freedom Multiple R-squared: 0.5089, Adjusted R-squared: 0.4936

F-statistic: 33.16 on 3 and 96 DF, p-value: 8.49e-15

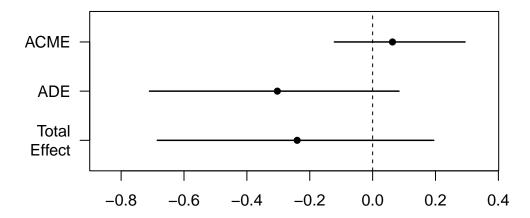
#### Running a Mediation Analysis in R

```
#Regress M on X
outcomeM_fit <- lm(mediator1 ~ condition, data = df)
summary(outcomeM_fit)

#Regress Y on M and X
outcomeY_fit <- lm(outcome ~ mediator1 + condition, data = df)
summary(outcomeY_fit)

3
summary(outcomeY_fit)</pre>
4
```

- (1) Run a regression of the M (mediator) on X using the lm() function
- 2 Show output of the M on X regression using the summary() function
- 3 Run a regression of Y on M and X using the lm() function
- (4) Show output of the Y on M and X regression using the summary() function
- (5) Run a mediation using the two regressions above. treat is the name of your X condition. mediator is the name of your mediating variable. Setting boot to TRUE will ensure that your mediation is bootstrapped. Lastly, the sims argument tells R how many samples you wish to bootstrap from. Typically you want ~ 5000 or more.
- (6) For a summary of your mediation, use the summary() function. The indirect effect is labeled ACME
- (7) The plot() function here will give you a graphical representation of the output above with respect to the range of the confidence interval for each metric. Please note by default this is the 95% confidence interval



Call:
lm(formula = mediator1 ~ condition, data = df)

#### Residuals:

Min 1Q Median 3Q Max -2.860 -0.755 0.140 1.140 2.280

#### Coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 7.0000 0.3412 20.515 <2e-16 \*\*\*

condition -0.1400 0.2158 -0.649 0.518

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.079 on 98 degrees of freedom

Multiple R-squared: 0.004276, Adjusted R-squared: -0.005884

F-statistic: 0.4209 on 1 and 98 DF, p-value: 0.518

#### Call:

lm(formula = outcome ~ mediator1 + condition, data = df)

#### Residuals:

Min 1Q Median 3Q Max -2.2245 -0.5522 -0.0769 0.4724 3.4724

#### Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 53.53460 0.74376 71.979 < 2e-16 \*\*\*

mediator1 -0.45066 0.09569 -4.709 8.28e-06 \*\*\*

condition -0.30309 0.20487 -1.479 0.142

\_\_\_

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.022 on 97 degrees of freedom Multiple R-squared: 0.1954, Adjusted R-squared: 0.1788

F-statistic: 11.78 on 2 and 97 DF,  $\,$  p-value: 2.634e-05

#### Causal Mediation Analysis

 ${\tt Nonparametric\ Bootstrap\ Confidence\ Intervals\ with\ the\ Percentile\ Method}$ 

Estimate 95% CI Lower 95% CI Upper p-value

ACME 0.0631 -0.1217 0.29 0.52 ADE -0.3031 -0.7098 0.08 0.12 Total Effect -0.2400 -0.6849 0.19 0.28 Prop. Mediated -0.2629 -6.0955 4.66 0.76

Sample Size Used: 100

Simulations: 5000

#### **Assumptions of Moderation Analyses**

```
# Residual Normality
shapiro.test(residuals(moderation))

# Multicollinearity
car::vif(moderation, type = c("predictor"))

# Independence of Errors
car::durbinWatsonTest(moderation)

3
```

- 1 Test of the residual normality of the moderation using the shapiro.test() function
- ② Test of the multicollinearity of the moderation analyses using the vif() function in the car package. Because there is an interaction, you must specify an additional argument of type = c("predictor") to properly account for the interaction effect.
- (3) To test the independence of errors assumption, you can do so using the durbinWatsonTest() function from the car package.

Shapiro-Wilk normality test

data: residuals(moderation)
W = 0.98684, p-value = 0.4272

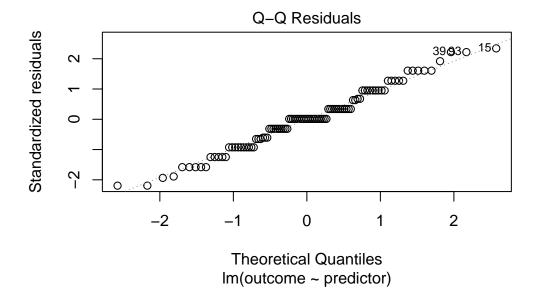
GVIF Df GVIF^(1/(2\*Df)) Interacts With Other Predictors condition 1 3 1 predictor -- predictor 1 3 1 condition -- lag Autocorrelation D-W Statistic p-value 1 -0.02268275 2.029087 0.756

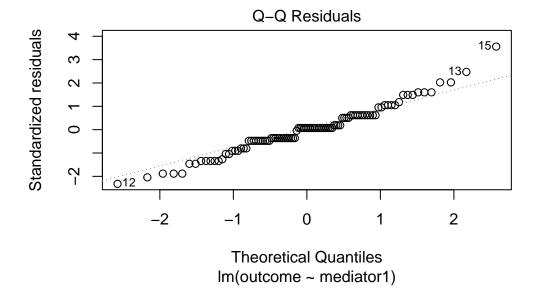
Alternative hypothesis: rho != 0

#### **Assumptions of Mediation Analyses**

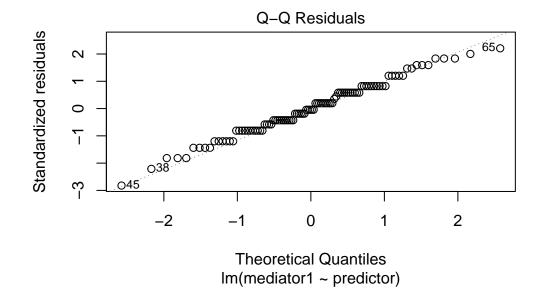
```
# Linearity
plot(lm(outcome ~ predictor, data = df),2)
①
```

2 To assess multicollinearity, the best course of action is a simple correlation matrix. You can achieve this using the cor() function for a correlation matrix









mediator1 outcome predictor condition mediator1 1.00000000 -0.4210068 -0.38328907 -0.06539201

```
outcome -0.42100683 1.0000000 0.71129322 -0.10692147 predictor -0.38328907 0.7112932 1.00000000 -0.07432941 condition -0.06539201 -0.1069215 -0.07432941 1.00000000
```

# Using Moderation and Mediation Usings Hayes PROCESS Macro (for R)

Click on the following link to download the R script for the PROCESS macro for R.

#### A Moderation Example Using Hayes PROCESS Macro

- (1) Assign your data to the data argument
- 2 Assign your outcome variable to the y argument
- 3 Assign your predictor variable to the x argument
- 4 Assign your moderator to the w argument
- (5) Set your model argument to 1 for simple moderation
- (6) The stand = 1 argument standardizes your output

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* PROCESS for R Version 4.3.1 \*\*\*\*\*\*\*\*\*\*\*\*\*\*

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

\*

Model: 1

Y : outcome
X : predictor
W : mediator1

Sample size: 100

\*

Outcome Variable: outcome

Model Summary:

R R-sq MSE F df1 df2 p 0.7294 0.5320 0.6141 36.3739 3.0000 96.0000 0.0000

Model:

	coeff	se	t	р	LLCI	ULCI
constant	47.3198	3.6872	12.8336	0.0000	40.0008	54.6389
predictor	0.5567	0.5256	1.0592	0.2922	-0.4866	1.6001
mediator1	-0.2975	0.5240	-0.5676	0.5716	-1.3377	0.7427
Int 1	0.0169	0.0761	0.2222	0.8246	-0.1341	0.1679

Product terms key:

Int\_1 : predictor x mediator1

Test(s) of highest order unconditional interaction(s):

R2-chng F df1 df2 p X\*W 0.0002 0.0494 1.0000 96.0000 0.8246

\*\*\*\*\*\*\*\*\*\*\*\*\*\* ANALYSIS NOTES AND ERRORS \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Level of confidence for all confidence intervals in output: 95

NOTE: Standardized coefficients not available for models with moderators.



The Hayes PROCESS for R requires that all data is numeric in nature. As such, ensure that any potential factor variables are numeric prior to running the analyses. A failure to do so will result in PROCESS not running.

#### A Mediation Example Using Hayes PROCESS Macro

```
process(data = df,
    y = "outcome",
    x = "predictor",
    m = "mediator1",
    model = 4,
    stand = 1,
    boot = 5000)
(1)

(2)

(3)

(3)

(4)

(6)

(6)

(7)
```

- (1) Assign your data to the data argument
- (2) Assign your outcome variable to the y argument
- (3) Assign your predictor variable to the x argument
- (4) Assign your mediator to the m argument
- (5) Set your model argument to 4 for simple mediation
- (6) The stand = 1 argument standardizes your output
- (7) The boot argument specifies the number of samples you wish to bootstrap

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* PROCESS for R Version 4.3.1 \*\*\*\*\*\*\*\*\*\*\*\*\*\*

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

\*

Model: 4

Y : outcome
X : predictor
M : mediator1

Sample size: 100

Random seed: 818206

**************************************						
Model Summa	rv:					
R	•	MSE	F	df1	df2	р
0.3833	-	0.9975	16.8766	1.0000	98.0000	0.0001
Model:						
	coeff	se	t	р	LLCI	ULCI
constant	9.4738	0.6609	14.3352	0.0000	8.1623	10.7852
predictor	-0.3812	0.0928	-4.1081	0.0001	-0.5654	-0.1971
Standardize		nts:				
	coeff					
predictor	-0.3833					
	******		*******	*****	******	******
Outcome Var	lable: outc	ome				
Model Cumme						
Model Summa R	•	MSE	F	df1	df2	<b>n</b>
0.7292	-	0.6081	55.0760	2.0000	97.0000	0.0000
0.1292	0.5517	0.0001	33.0700	2.0000	97.0000	0.0000
Model:						
	coeff	se	t	р	LLCI	ULCI
constant	46.5259	0.9080	51.2386	0.0000	44.7237	48.3281
predictor	0.6722	0.0784	8.5694	0.0000	0.5165	0.8279
mediator1	-0.1824	0.0789	-2.3121	0.0229	-0.3389	-0.0258
mcaiatori	0.1021	0.0703	2.0121	0.0220	0.0000	0.0200
Standardize	d coefficie	nts:				
	coeff					
predictor	0.6446					
mediator1	-0.1740					
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******** DIRECT AND INDIRECT EFFECTS OF X ON Y *************
Direct effect of X on Y:
  effect
                          LLCI
                               ULCI
                                    c'_cs
          se
                t
                      p
  0.6722
        0.0784
                   0.0000
                         0.5165
                              0.8279
                                    0.6446
             8.5694
Indirect effect(s) of X on Y:
       Effect
            BootSE BootLLCI BootULCI
mediator1
       0.0695
            0.0353
                  0.0100
                        0.1483
Completely standardized indirect effect(s) of X on Y:
       Effect
            BootSE BootLLCI BootULCI
mediator1
       0.0667
            0.0339
                  0.0097
                       0.1436
************ ANALYSIS NOTES AND ERRORS ***************
Level of confidence for all confidence intervals in output: 95
Number of bootstraps for percentile bootstrap confidence intervals: 5000
```