# Mediation

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PSY 653 Module 8 Lab
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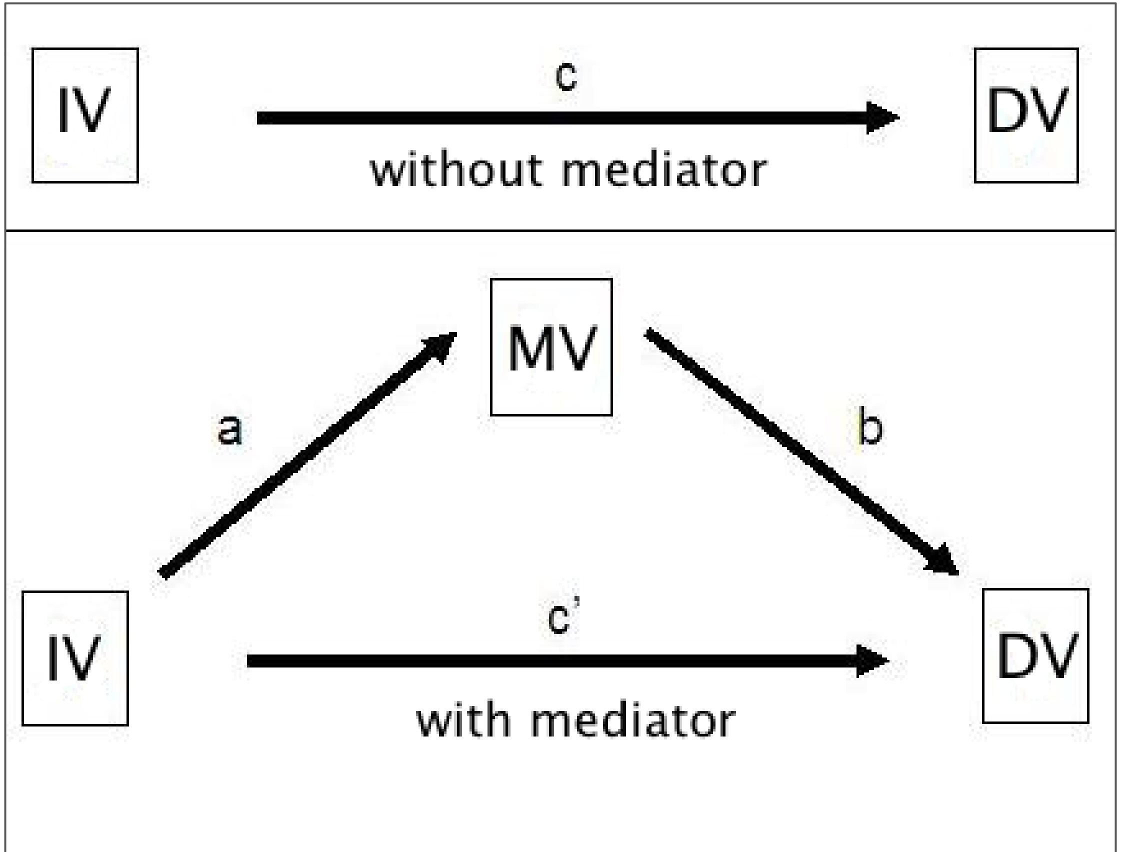
# The “paths” in mediation



# Baron & Kenny criteria for testing mediation

1. Show X is related to Y **(c path)**
2. Show X is related to M **(a path)**
3. Show Y is related to M **(b path)**
4. Show that M explains the relationship between X and Y **(c' path)**
   - One way to do this is to show that controlling for M will cause $r_{xy}$ to go toward zero

*Must meet ***all*** criteria to run a mediation model

# Load Libraries

```
# Load libraries
```{r,message=FALSE}
install.packages("mediation")

library(tidyverse)
library(psych)
library(mediation)
library(ppcor)
```
```

# Read in data

````
# Read in data
```{r}
med <- read_csv("mediate2.csv")
```
````

```
Parsed with column specification:
cols(
  X1 = col_double(),
  X2 = col_double(),
  X3 = col_double(),
  X4 = col_double(),
  X5 = col_double(),
  Y1 = col_double()
)
```

This is a simulated dataset with four predictor variables (X1-X5) and one outcome variable (Y1)

Note: though not shown here, don't forget to do your data management "best practices" by examining descriptives and visualizing data before conducting analyses!

# Examine correlations between variables

```{r}
cor(med)
```

```
           X1          X2         X3         X4         X5         Y1
X1 1.00000000  0.03946291 0.03657073 0.04344269  0.1020180  0.3465506
X2 0.03946291  1.00000000 0.08889150 0.06447405 -0.1310097 -0.3227619
X3 0.03657073  0.08889150 1.00000000 0.34246913  0.7331822  0.5053060
X4 0.04344269  0.06447405 0.34246913 1.00000000  0.4068431  0.4104644
X5 0.10201803 -0.13100973 0.73318217 0.40684310  1.0000000  0.6405100
Y1 0.34655064 -0.32276194 0.50530603 0.41046440  0.6405100  1.0000000
```

# Analysis 1: Test the hypothesis that X4 mediates the relationship between X1 and Y1

# Step 1: Determine if mediation is plausible, based on the Baron & Kenny Criteria

Examine correlations between variables

```{r}
cor(med)
```

| | x1 | x2 | x3 | x4 | x5 | Y1 |
|---|---|---|---|---|---|---|
| x1 | 1.00000000 | 0.03946291 | 0.03657073 | 0.04344269 | 0.1020180 | 0.3465506 |
| x2 | 0.03946291 | 1.00000000 | 0.08889150 | 0.06447405 | -0.1310097 | -0.3227619 |
| x3 | 0.03657073 | 0.08889150 | 1.00000000 | 0.34246913 | 0.7331822 | 0.5053060 |
| x4 | 0.04344269 | 0.06447405 | 0.34246913 | 1.00000000 | 0.4068431 | 0.4104644 |
| x5 | 0.10201803 | -0.13100973 | 0.73318217 | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | 0.50530603 | 0.41046440 | 0.6405100 | 1.0000000 |

**rxy = .3466 (c path)**

**rxm = .0434 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis? (Baron & Kenny criteria)

````
```{r}
cor(med)
```
````

```
           X1          X2         X3         X4         X5         Y1
X1 1.00000000  0.03946291 0.03657073 0.04344269  0.1020180  0.3465506
X2 0.03946291  1.00000000 0.08889150 0.06447405 -0.1310097 -0.3227619
X3 0.03657073  0.08889150 1.00000000 0.34246913  0.7331822  0.5053060
X4 0.04344269  0.06447405 0.34246913 1.00000000  0.4068431  0.4104644
X5 0.10201803 -0.13100973 0.73318217 0.40684310  1.0000000  0.6405100
Y1 0.34655064 -0.32276194 0.50530603 0.41046440  0.6405100  1.0000000
```

**rxy = .3466 (c path)**

**rxm = .0434 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis? (Baron & Kenny criteria)

````
```{r}
cor(med)
```
````

| | x1 | x2 | [illegible] | x4 | x5 | Y1 |
|---|---|---|---|---|---|---|
| x1 | 1.00000000 | 0.03946291 | [illegible] | [illegible] | 0.1020180 | 0.3465506 |
| x2 | 0.03946291 | 1.00000000 | [illegible] | [illegible] | -0.1310097 | -0.3227619 |
| x3 | 0.03657073 | 0.08889150 | [illegible] | [illegible] | 0.7331822 | 0.5053060 |
| x4 | 0.04344269 | 0.06447405 | [illegible] | 1.00000000 | 0.4068431 | 0.4104644 |
| x5 | 0.10201803 | -0.13100973 | [illegible] | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | [illegible] | 0.41046440 | 0.6405100 | 1.0000000 |

**NO!**

**rxy = .3466 (c path)**

**rxm = .0434 (a path)**

**rmy = .4105 (b path)**

Negligible correlation

# Analysis 2: Test the hypothesis that X4 mediates the relationship between X3 and Y1

# Step 1: Determine if mediation is plausible, based on the Baron & Kenny Criteria

```{r}
cor(med)
```

| | X1 | X2 | X3 | X4 | X5 | Y1 |
|---|---|---|---|---|---|---|
| X1 | 1.00000000 | 0.03946291 | 0.03657073 | 0.04344269 | 0.1020180 | 0.3465506 |
| X2 | 0.03946291 | 1.00000000 | 0.08889150 | 0.06447405 | -0.1310097 | -0.3227619 |
| X3 | 0.03657073 | 0.08889150 | 1.00000000 | 0.34246913 | 0.7331822 | 0.5053060 |
| X4 | 0.04344269 | 0.06447405 | 0.34246913 | 1.00000000 | 0.4068431 | 0.4104644 |
| X5 | 0.10201803 | -0.13100973 | 0.73318217 | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | 0.50530603 | 0.41046440 | 0.6405100 | 1.0000000 |

**rxy = .5053 (c path)**

**rxm = .3425 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis? (Baron & Kenny criteria)

```
```{r}
cor(med)
```
```

| | X1 | X2 | X3 | X4 | X5 | Y1 |
|---|---|---|---|---|---|---|
| X1 | 1.00000000 | 0.03946291 | 0.03657073 | 0.04344269 | 0.1020180 | 0.3465506 |
| X2 | 0.03946291 | 1.00000000 | 0.08889150 | 0.06447405 | -0.1310097 | -0.3227619 |
| X3 | 0.03657073 | 0.08889150 | 1.00000000 | 0.34246913 | 0.7331822 | 0.5053060 |
| X4 | 0.04344269 | 0.06447405 | 0.34246913 | 1.00000000 | 0.4068431 | 0.4104644 |
| X5 | 0.10201803 | -0.13100973 | 0.73318217 | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | 0.50530603 | 0.41046440 | 0.6405100 | 1.0000000 |

**rxy = .5053 (c path)**

**rxm = .3425 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis? (Baron & Kenny criteria)

````
```{r}
cor(med)
```
````

| | X1 | X2 | X3 | X4 | X5 | Y1 |
|---|---|---|---|---|---|---|
| X1 | 1.00000000 | 0.03946291 | 0.03[illegible]7073 | 0.[illegible]4269 | 0.1020180 | 0.3465506 |
| X2 | 0.03946291 | 1.00000000 | 0.[illegible]89[illegible]0 | 0.[illegible]6447405 | -0.1310097 | -0.3227619 |
| X3 | 0.03657073 | 0.08889150 | [illegible]00[illegible]000 | [illegible].34246913 | 0.7331822 | 0.5053060 |
| X4 | 0.04344269 | 0.06447405 | [illegible]3424[illegible] | 1.00000000 | 0.4068431 | 0.4104644 |
| X5 | 0.10201803 | -0.131009[illegible] | [illegible]73318217 | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | 0.[illegible]530603 | 0.41046440 | 0.6405100 | 1.0000000 |

**YES!**

All paths have moderate correlations

rxy = .5053 (c path)

rxm = .3425 (a path)

rmy = .4105 (b path)

# Step 2: Use semi-partial correlation to examine correlation between X and Y when partialling out the effect of the mediator

```{r}
spcor.test(x = med$X3, y = med$Y1, z = med$X4)
```

| estimate <dbl> | p.value <dbl> | statistic <dbl> | n <int> | gp <dbl> | Method <fctr> |
|---|---|---|---|---|---|
| 0.3999824 | 2.030191e-24 | 10.66313 | 600 | 1 | pearson |

1 row

(Baron & Kenny Criteria, continued)

# Step 2.1: Compare semi-partial correlation to rxy (Baron & Kenny criteria)

```{r}
spcor.test(x = med$X3, y = med$Y1, z = med$X4)
```

| estimate <dbl> | p.value <dbl> | statistic <dbl> | n <int> | gp <dbl> | Method <fctr> |
|---|---|---|---|---|---|
| 0.3999824 | 2.030191e-24 | 10.66313 | 600 | 1 | pearson |

1 row

**Compare to rxy = .5053 (from previous slide)**

**r y(x.m) = 0.3999. This is 0.11 smaller than rxy (0.5053), indicating that partial mediation is plausible. In other words, there is a portion of the relation between x and y that involves m.**

# Step 3: Compare models via hierarchical regression

````
### Regression method
```{r}
m1 <- lm(Y1 ~ X3      , data = med)
m2 <- lm(Y1 ~ X3 + X4 , data = med)

anova(m1,m2)

```
````

```
Analysis of Variance Table

Model 1: Y1 ~ X3
Model 2: Y1 ~ X3 + X4
  Res.Df    RSS Df Sum of Sq      F    Pr(>F)    
1    598 373.91                                  
2    597 341.85  1    32.062 55.993 2.617e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

m1 just regresses the outcome (Y1) on the predictor (X3)

m2 regresses the outcome (Y1) on both the predictor (X3) and the hypothesized mediator (X4)

m2 explains significantly more variance in the outcome than m1

# Step 4: Test mediation model via psych::mediate

```
### mediate in psych
```{r}

fitmed <- psych::mediate(Y1 ~ X3 + (X4), data = med)
summary(fitmed)

```
```

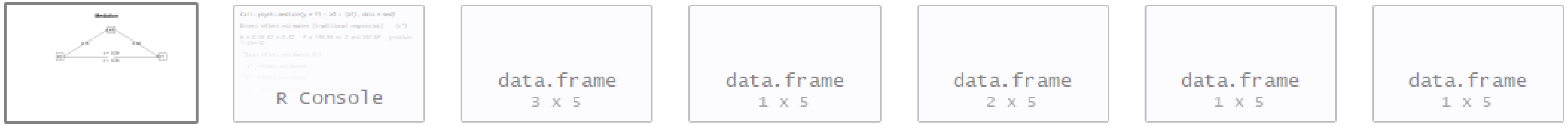
- **psych::mediate: mediate function (via psych package)**
- **Y1: Outcome variable**
- **X3: Predictor variable**
- **(X4): Mediator variable (keep it enclosed in parentheses)**
- **data = med: dataset**

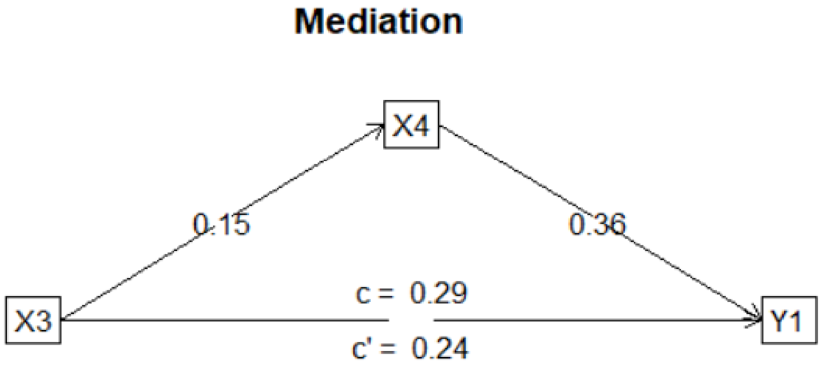
```
### mediate in psych
```{r}

fitmed <- psych::mediate(Y1 ~ X3 + (X4), data = med)
summary(fitmed)

```
```

1 2 3 4 5 6 7



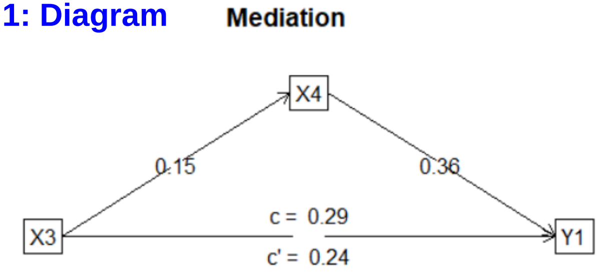




**WINDOWS**

1. Model diagram with paths
2. Function call
3. c’ path
4. c path
5. a path
6. b path
7. ab bootstrapped results (indirect effect)

# psych::mediate output windows

**1: Diagram**




**2: Function Call**

```
Call: psych::mediate(y = Y1 ~ X3 + (X4), data = med)

Direct effect estimates (traditional regression)    (c')

R = 0.56 R2 = 0.32   F = 139.95 on 2 and 597 DF   p-value:  1.44e-50

 Total effect estimates (c)

 'a'  effect estimates

 'b'  effect estimates

 'ab'  effect estimates (through mediators)
```

**3: c' path**

| | Y1 <dbl> |
|---|---|
| Intercept | 1.52 |
| X3 | 0.24 |
| X4 | 0.36 |

3 rows

**4: c path**

| | Y1 <dbl> |
|---|---|
| X3 | 0.29 |

1 row

**5: a path**

| | X4 <dbl> |
|---|---|
| Intercept | 2.15 |
| X3 | 0.15 |

2 rows

**6: b path**

| | Y1 <dbl> |
|---|---|
| X4 | 0.36 |

1 row

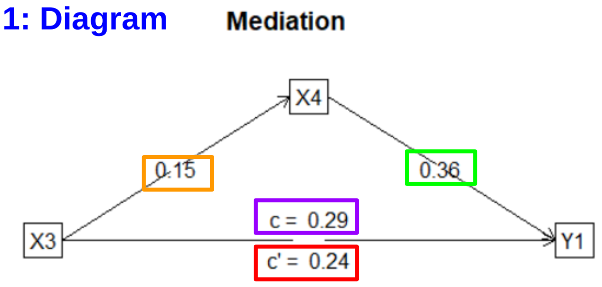
**7: a*b path bootstrapped analysis (indirect effect)**

| | Y1 | boot <dbl> | sd <dbl> | lower <dbl> | upper <dbl> |
|---|---|---|---|---|---|
| X3 | 0.05 | 0.05 | 0.01 | 0.04 | 0.07 |

1 row

# psych::mediate output windows

**1: Diagram**




**2: Function Call**

```
Call: psych::mediate(y = Y1 ~ X3 + (X4), data = med)

Direct effect estimates (traditional regression)    (c')

R = 0.56 R2 = 0.32   F = 139.95 on 2 and 597 DF   p-value:  1.44e-50

 Total effect estimates (c)

 'a'  effect estimates

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 'ab'  effect estimates (through mediators)
```

**3: c' path**

| | Y1 <dbl> |
|---|---|
| Intercept | 1.52 |
| X3 | 0.24 |
| X4 | 0.36 |

3 rows

**4: c path**

| | Y1 <dbl> |
|---|---|
| X3 | 0.29 |

1 row

**5: a path**

| | X4 <dbl> |
|---|---|
| Intercept | 2.15 |
| X3 | 0.15 |

2 rows

**6: b path**

| | Y1 <dbl> |
|---|---|
| X4 | 0.36 |

1 row

**7: a*b path bootstrapped analysis (indirect effect)**

| | Y1 <dbl> | boot <dbl> | sd <dbl> | lower <dbl> | upper <dbl> |
|---|---|---|---|---|---|
| X3 | 0.05 | 0.05 | 0.01 | 0.04 | 0.07 |

1 row

Bootstrapped estimate

Evidence of partial mediation

# psych::mediate a*b interpretation

To evaluate if the indirect effect is significant:

**Output Window 7: a*b path bootstrapped analysis (indirect effect)**

| | Y1 <dbl> | boot <dbl> | sd <dbl> | lower <dbl> | upper <dbl> |
|---|---|---|---|---|---|
| X3 | 0.05 | 0.05 | 0.01 | 0.04 | 0.07 |

1 row

**Does the bootstrapped confidence interval for the indirect effect (aka a path estimate * b path estimate) contain zero?**

**In this case it does not, indicating that X4 partially mediates the relation between X3 and Y1.**

You can calculate the proportion of the relation of Y1 on X3 that is mediated by X4 by dividing the indirect effect by the total effect:
Proportion mediated = (a*b)/c
Proportion mediated = 0.05/0.29 = .1862. 18.6% of the effect is mediated.

# Step 5: Test mediation via mediation::mediate

```r
### Mediate in mediation package
```{r}
fitM <- lm(X4 ~ X3, data = med)
fitY <- lm(Y1 ~ X3 + X4, data = med)


fitmed <- mediation::mediate(fitM, fitY, treat = "X3", mediator = "X4")
summary(fitmed)

```
```

```
Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals
```

| | Estimate | 95% CI Lower | 95% CI Upper | p-value |
|---|---|---|---|---|
| ACME | 0.0535 | 0.0366 | 0.07 | <2e-16 *** |
| ADE | 0.2405 | 0.2002 | 0.28 | <2e-16 *** |
| Total Effect | 0.2940 | 0.2515 | 0.33 | <2e-16 *** |
| Prop. Mediated | 0.1806 | 0.1246 | 0.24 | <2e-16 *** |

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 600


Simulations: 1000
```

This is an alternative function() for testing mediation. Both work!

1. Regress mediator variable (X4) on predictor variable (X3)
1. Regress outcome variable (Y1) on predictor (X3) and mediator (X4)
1. Use mediation::mediate to test models for mediation. Indicate predictor variable (treat = “X3”) and mediator variable (mediator = “X4”)

# Step 5: Test mediation via mediation::mediate

```r
### Mediate in mediation package
```{r}
fitM <- lm(X4 ~ X3, data = med)
fitY <- lm(Y1 ~ X3 + X4, data = med)


fitmed <- mediation::mediate(fitM, fitY, treat = "X3", mediator = "X4")
summary(fitmed)

```
```

```
Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals

               Estimate 95% CI Lower 95% CI Upper p-value    
ACME             0.0535       0.0366         0.07  <2e-16 ***
ADE              0.2405       0.2002         0.28  <2e-16 ***
Total Effect     0.2940       0.2515         0.33  <2e-16 ***
Prop. Mediated   0.1806       0.1246         0.24  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 600


Simulations: 1000
```

**ACME**: “Average Causal Mediated Effect.” This is the effect of the mediator alone (ab bootstrapped; equivalent to window 7 via psych::mediate)

**ADE**: “Average Direct Effect” (c’ path; equivalent to window 3 via psych::mediate)

**Total Effect**: c path (equivalent to window 4 via psych::mediate)

**Prop. Mediated**: Proportion of variance explained by the mediator. *(a path*b path)/c path*

# Analysis 3: Test the hypothesis that X4 mediates the relationship between X5 and Y1

# Determine if mediation is plausible, based on the Baron & Kenny Criteria

```{r}
cor(med)
```

```
           X1          X2         X3         X4         X5         Y1
X1 1.00000000  0.03946291 0.03657073 0.04344269  0.1020180  0.3465506
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X4 0.04344269  0.06447405 0.34246913 1.00000000  0.4068431  0.4104644
X5 0.10201803 -0.13100973 0.73318217 0.40684310  1.0000000  0.6405100
Y1 0.34655064 -0.32276194 0.50530603 0.41046440  0.6405100  1.0000000
```

**rxy = .6405 (c path)**

**rxm = .4068 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis?

```{r}
cor(med)
```

| | X1 | X2 | X3 | X4 | X5 | Y1 |
|---|---|---|---|---|---|---|
| X1 | 1.00000000 | 0.03946291 | 0.03657073 | 0.04344269 | 0.1020180 | 0.3465506 |
| X2 | 0.03946291 | 1.00000000 | 0.08889150 | 0.06447405 | -0.1310097 | -0.3227619 |
| X3 | 0.03657073 | 0.08889150 | 1.00000000 | 0.34246913 | 0.7331822 | 0.5053060 |
| X4 | 0.04344269 | 0.06447405 | 0.34246913 | 1.00000000 | 0.4068431 | 0.4104644 |
| X5 | 0.10201803 | -0.13100973 | 0.73318217 | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | 0.50530603 | 0.41046440 | 0.6405100 | 1.0000000 |

**rxy = .6405 (c path)**

**rxm = .4068 (a path)**

**rmy = .4105 (b path)**

# Do we have justification to test the mediation hypothesis?

```{r}
cor(med)
```

| | X1 | X2 | X3 | X4 | X5 | Y1 |
|---|---|---|---|---|---|---|
| X1 | 1.00000000 | 0.03946291 | [illegible] | [illegible] | 0.1020180 | 0.3465506 |
| X2 | 0.03946291 | 1.00000000 | [illegible] | 0.06447405 | -0.1310097 | -0.3227619 |
| X3 | 0.03657073 | 0.08889150 | [illegible] | 0.34246913 | 0.7331822 | 0.5053060 |
| X4 | 0.04344269 | [illegible] | [illegible] | 1.00000000 | 0.4068431 | 0.4104644 |
| X5 | 0.10201803 | [illegible] | [illegible] | 0.40684310 | 1.0000000 | 0.6405100 |
| Y1 | 0.34655064 | -0.32276194 | [illegible] | 0.41046440 | 0.6405100 | 1.0000000 |

YES!

All paths have moderate correlations

**rxy = .6405 (c path)**

**rxm = .4068 (a path)**

**rmy = .4105 (b path)**

# Step 2.1: Use semi-partial correlation to examine correlation between X and Y when partialling out the effect of the mediator

```{r}
spcor.test(x = med$X5, y = med$Y1, z = med$X4)
```

| estimate | p.value | statistic | n | gp | Method |
|---|---|---|---|---|---|
| <dbl> | <dbl> | <dbl> | <int> | <dbl> | <fctr> |
| 0.5192757 | 1.150621e-42 | 14.84632 | 600 | 1 | pearson |

1 row

# Step 2.1: Compare semi-partial correlation to rxy (Baron & Kenny criteria)

````
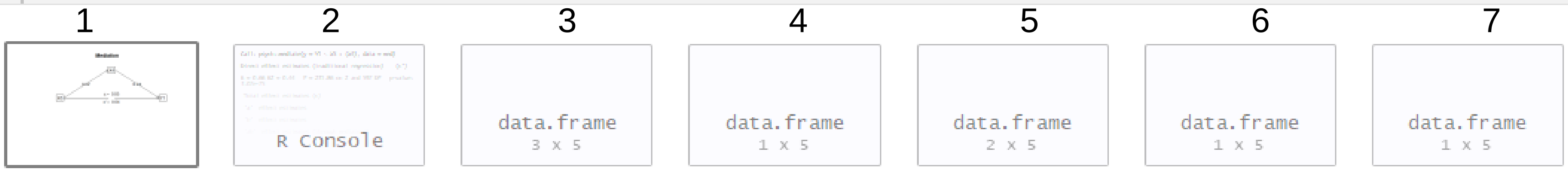
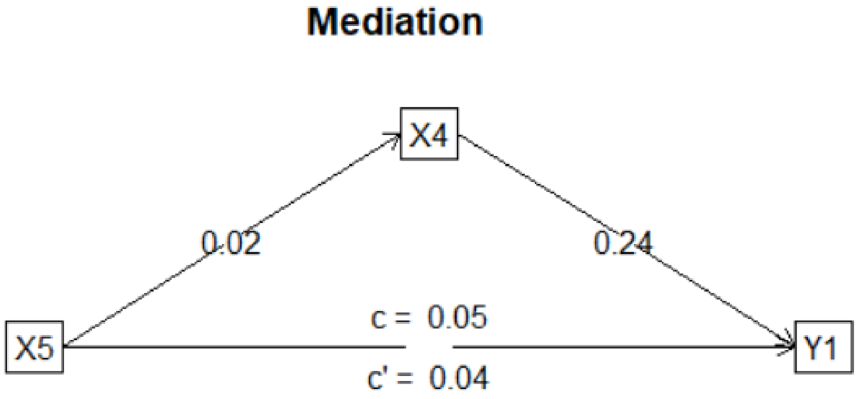
```{r}
spcor.test(x = med$X5, y = med$Y1, z = med$X4)
```
````

| estimate <dbl> | p.value <dbl> | statistic <dbl> | n <int> | gp <dbl> | Method <fctr> |
|---|---|---|---|---|---|
| 0.5192757 | 1.150621e-42 | 14.84632 | 600 | 1 | pearson |

1 row

**Compare to rxy = .6405 (from previous slide)**

**r y(x.m) = 0.5193. This is 0.12 smaller than rxy (0.6405), indicating that partial mediation is plausible. In other words, there is a portion of the relation between x and y that involves m.**

# Step 3: Compare models via hierarchical regression

```
### Regression method
```{r}
m1 <- lm(Y1 ~ X5       , data = med)
m2 <- lm(Y1 ~ X5 + X4 , data = med)

anova(m1,m2)

```
```

```
Analysis of Variance Table

Model 1: Y1 ~ X5
Model 2: Y1 ~ X5 + X4
  Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1    598 296.12
2    597 282.61  1    13.517 28.553 1.299e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

m2 explains significantly more variance in the outcome than m1

# Step 4: Test mediation model via psych::mediate

````
### mediate in psych
```{r}

fitmed <- psych::mediate(Y1 ~ X5 + (X4), data = med)
summary(fitmed)

```
````

- **psych::mediate: mediate function (via psych package)**
- **Y1: Outcome variable**
- **X5: Predictor variable**
- **(X4): Mediator variable (keep it enclosed in parentheses)**
- **data = med: dataset**

````
### mediate in psych
```{r}

fitmed <- psych::mediate(Y1 ~ X5 + (X4), data = med)
summary(fitmed)

```
````




**WINDOWS**

1. Diagram
2. Function call
3. c' path
4. c path
5. a path
6. b path
7. ab bootstrapped results (indirect effect)

# psych::mediate window 7

```r
### mediate in psych
```{r}

fitmed <- psych::mediate(Y1 ~ X5 + (X4), data = med)
summary(fitmed)

```
```

R Console | data.frame 3 x 5 | data.frame 1 x 5 | data.frame 2 x 5 | data.frame 1 x 5 | data.frame 1 x 5

| | Y1 <dbl> | boot <dbl> | sd <dbl> | lower <dbl> | upper <dbl> |
|---|---|---|---|---|---|
| X5 | 0.01 | 0.01 | 0 | 0 | 0.01 |

1 row

Lacking evidence for partial mediation (bootstrapped 95% CI contains zero)

# Step 5: Test mediation via mediation::mediate

```r
### Mediate in mediation package
```{r}
fitM <- lm(X4 ~ X5, data = med)
fitY <- lm(Y1 ~ X5 + X4, data = med)


fitmed <- mediation::mediate(fitM, fitY, treat = "X5", mediator = "X4")
summary(fitmed)

```
```

```
Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals

               Estimate 95% CI Lower 95% CI Upper p-value    
ACME            0.00552      0.00343         0.01  <2e-16 ***
ADE             0.04265      0.03739         0.05  <2e-16 ***
Total Effect    0.04817      0.04346         0.05  <2e-16 ***
Prop. Mediated  0.11361      0.07107         0.16  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sample Size Used: 600


Simulations: 1000
```

**ACME**: "Average Causal Mediated Effect." This is the effect of the mediator alone (ab bootstrapped; Equivalent to window 7 via psych::mediate)

**ADE**: "Average Direct Effect" (c' path; equivalent ro window 3 via psych::mediate)

**Total Effect**: c path (Equivalent to window 4 via psych::mediate)

**Prop. Mediated**: Proportion of variance explained by the mediator. *(a path*b path)/c path*