WELCOME TO PSY 653 LAB!

MODULE 03:

MEDIATION

*Thanks to Gemma Wallace for her help with these slides

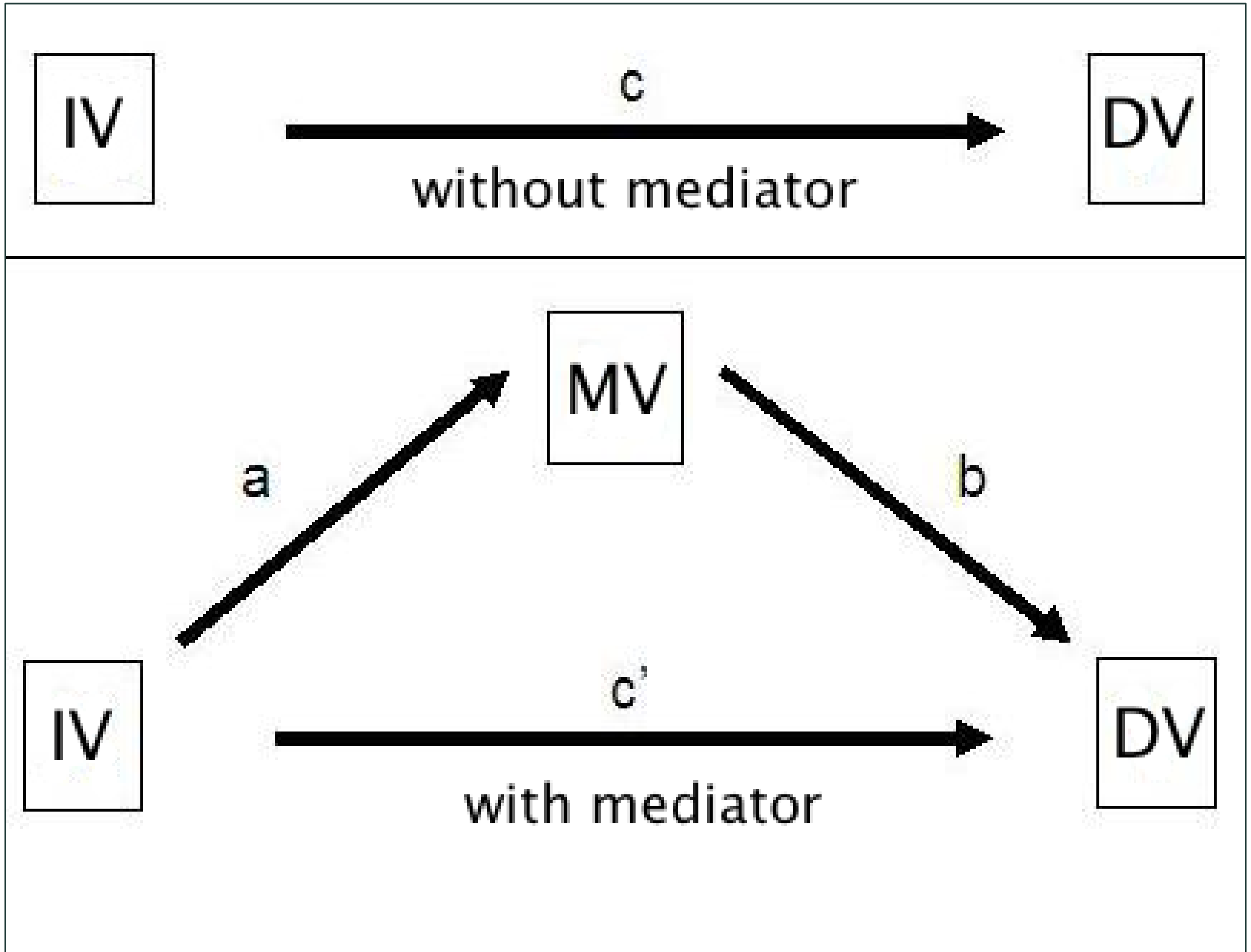
OBJECTIVES

- Explain mediation
- Discuss the Baron & Kenny Criteria for testing mediation
- Coding tutorial

MEDIATION

- A mediator variable is a variable that helps to explain the relationship between X & Y
- A mediated relationship occurs when a third variable plays an important role in governing the relationship between the two other variables
- We can have a full mediation (not likely in psychology) or a partial mediation model (more likely in psychology)

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

CREATE A NEW R-PROJECT AND R-NOTEBOOK!

Download the “mediate2.csv” file from Canvas and save it into your R-project file

LOAD LIBRARIES

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

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

STOP!

- **New R concept**:
  - We will be experiencing “Package conflicts” during this lab
  - In short, both the ***psych*** package and the ***mediation*** package have a function called “mediate()”
  - Therefore, we need to tell R which package to call the mediate() function from
    - To do this we use the package name followed by two colons and then the name of the function: “**package_name::function()**”
      - Every time we use the mediate() function we will have to tell R which package it comes from.

```
Attaching package: �mediation�

The following object is masked from �package:psych�:

    mediate
```

Continue on…

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!

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}
analysis1 <- select(med, X1, X4, Y1)
cor(analysis1)
```
```

```
           X1         X4        Y1
X1 1.00000000 0.04344269 0.3465506
X4 0.04344269 1.00000000 0.4104644
Y1 0.34655064 0.41046440 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}
analysis1 <- select(med, X1, X4, Y1)
cor(analysis1)
```
```

	X1	X4	Y1
X1	1.00000000	0.04344269	0.3465506
X4	0.04344269	1.00000000	0.4104644
Y1	0.34655064	0.41046440	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}
analysis1 <- select(med, [illegible], X4, Y1)
cor(analysis1)
```
```

```
            X1         X[illegible]         Y1
X1 1.0000000[illegible] 0.0[illegible]44269 0.3465506
X4 0.0434426[illegible] [illegible]0000 0.4104644
Y1 0.34655064 [illegible]41046440 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}
analysis2 <- select(med, X3, X4, Y1)
cor(analysis2)
```
```

```
          X3        X4        Y1
X3 1.0000000 0.3424691 0.5053060
X4 0.3424691 1.0000000 0.4104644
Y1 0.5053060 0.4104644 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}
analysis2 <- select(med, X3, X4, Y1)
cor(analysis2)
```
```

```
          X3        X4        Y1
X3 1.0000000 0.3424691 0.5053060
X4 0.3424691 1.0000000 0.4104644
Y1 0.5053060 0.4104644 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}
analysis2 <- select(med, X3, X4, Y1)
cor(analysis2)
```

	X3	X4	Y1
X3	1.0000000	0.[illegible]4691	0.5053060
X4	0.3424[illegible]	1.0000000	0.4104644
Y1	0.5053060	[illegible].4104644	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: TEST MEDIATION MODEL VIA PSYCH::MEDIATE

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

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

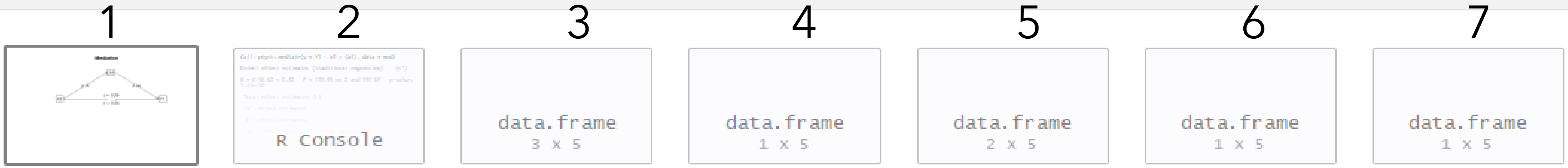
```
````

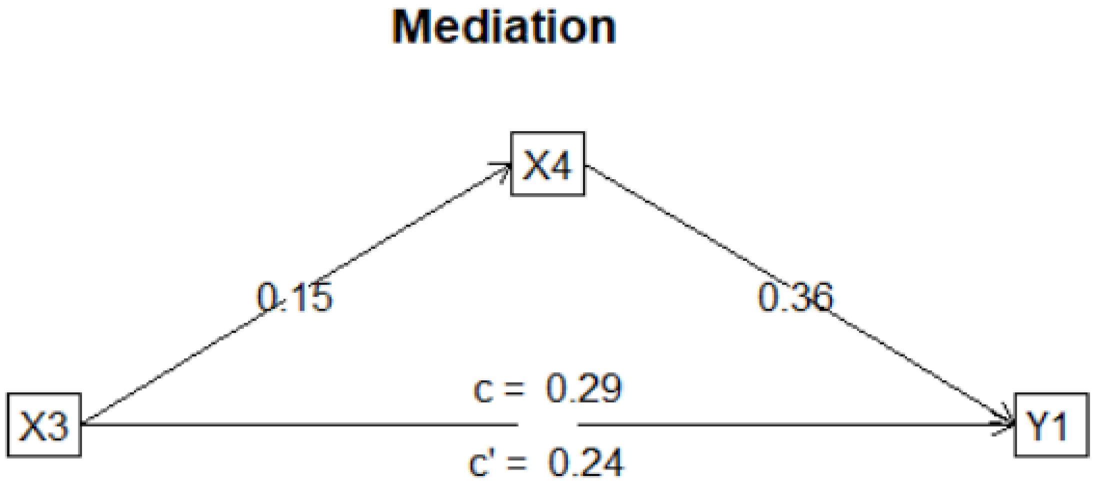
- **psych::mediate: mediate function (via psych package)**
- **Y1: Outcome variable**
- **X3: Predictor variable**
- **(X4): Mediator variable (keep it enclosed in parentheses)**
- **data = med: dataset**

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

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

```
```





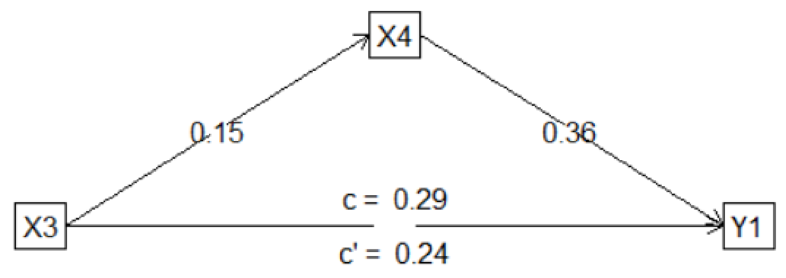
WINDOWS

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

Mediation



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)

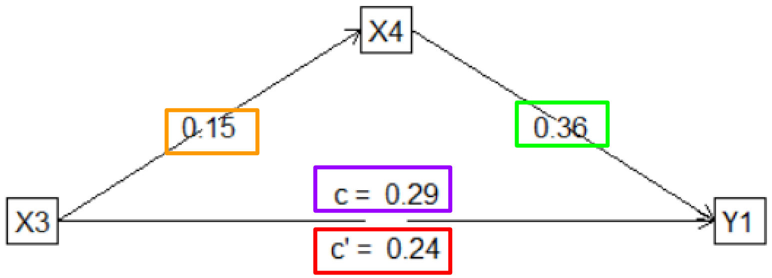
	Y1	boot	sd <dbl>	lower <dbl>	upper <dbl>
X3	0.05	0.05	0.01	0.04	0.07

1 row

PSYCH::MEDIATE OUTPUT WINDOWS

1: Diagram

Mediation



2: Function Call

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

Direct effect estimates (traditional regression)    (c')

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```

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)

	<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 = 0.054/0.29 = .1862. 18.6% of the effect is mediated.

STEP 4: TEST MEDIATION VIA MEDIATION::MEDIATE

```
### 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!

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

STEP 4: TEST MEDIATION VIA MEDIATION::MEDIATE

```
### 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
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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*