# EDUC 640

Introductory Statistics for Practitioners II

## Week 1

Introductions

- to each other and the course
- to some ways to think about our course content:
  - Designs that use ANOVA and *t*-tests
  - Simple and Multiple Regression
  - General Linear Model

# Designs that use ANOVA and *T*-tests

# Between-person Designs using *T*-tests

For example, a randomized experiment, for causal claims:

Posttest only equivalent groups design

| | | | |
|---|---|---|---|
| Treatment group | *R* | *X* | *O* |
| Control group | *R* | | *O* |

Or for non-randomized experiments, for association claims:

Posttest only **non**-equivalent groups design

| | | | |
|---|---|---|---|
| Treatment group | *NR* | *X* | *O* |
| Comparison group | *NR* | | *O* |

**Symbols Used in Experimental Designs**

*R* = randomly assigned

*NR* = **not** randomly assigned

*X* = treatment or intervention

*O* = Observation (i.e., the dependent variable AKA outcome variable)

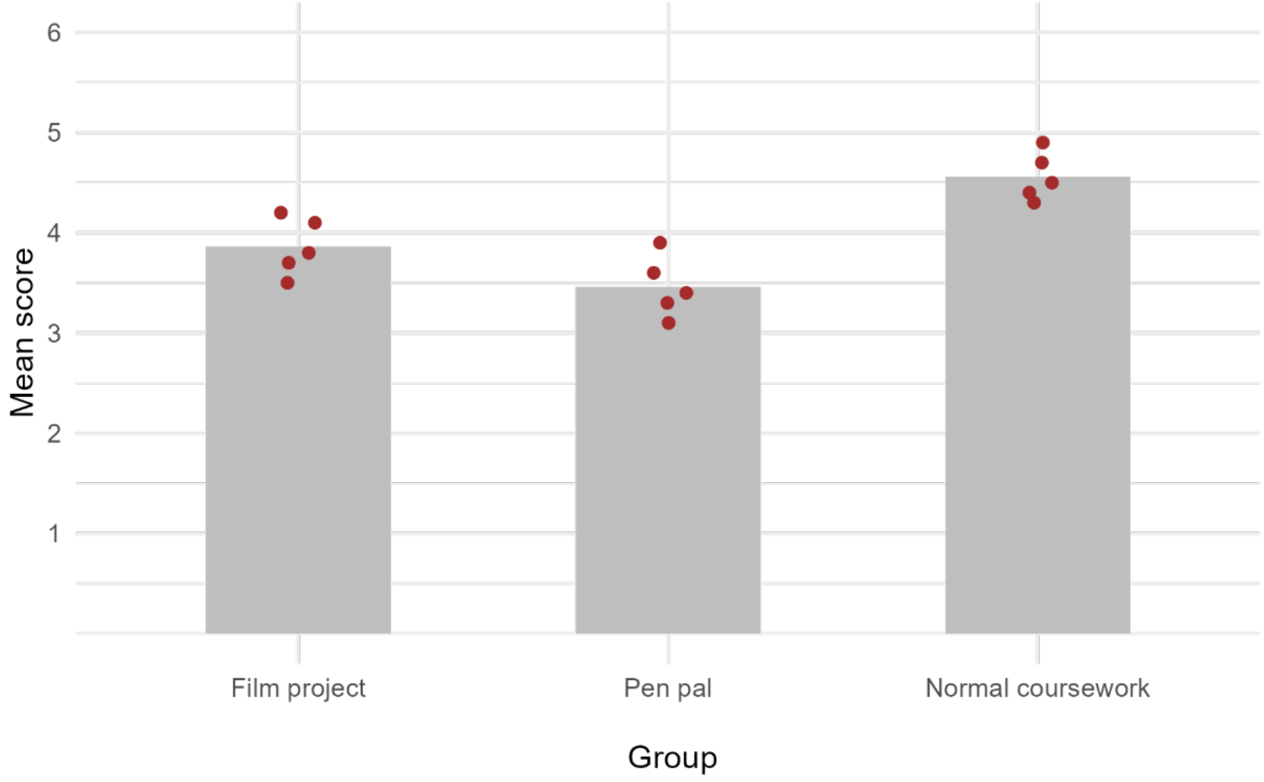
$O_1$ = Observation at time point 1

$O_2$ = Observation at time point 2, and so forth

For both of these designs, we can use an independent-sample's *t*-test.

# Between-person Designs using ANOVA

- For comparing groups' means on a continuous dependent variable.
- If only two-groups (i.e., two levels): **independent-samples *t*-test**
- For three or more levels: **One-way ANOVA**, AKA one-way between-subjects ANOVA.




| Group | *n* | *M* | *SD* |
|---|---|---|---|
| Film | 5 | 3.86 | 0.29 |
| Pen pal | 5 | 3.46 | 0.31 |
| Normal | 5 | 4.56 | 0.24 |
| Total | 15 | 3.96 | 0.54 |

Example is from Strunk and Mwavita (2020), Ch. 8

The word "subjects" is sometimes changed to "people" when people are the unit of analysis.

# Between-person Designs: Factorial ANOVA Designs

"Factorial" means that we can have more than one categorical variable and we can investigate how they *interact* with each other in regard to their association with the dependent variable.

***Design***

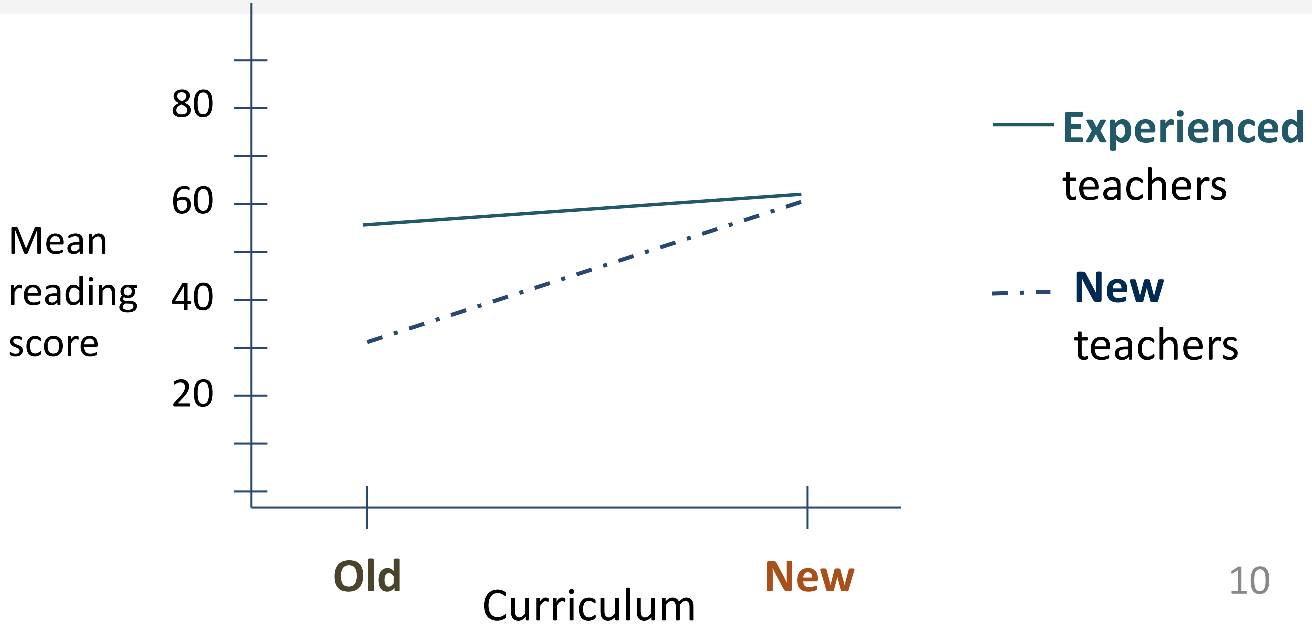
Old curriculum | New curriculum + Experienced teachers | New teachers →

| | |
|---|---|
| **Old** curriculum with **experienced** teachers | **New** curriculum with **experienced** teachers |
| **Old** curriculum with **new** teachers | **New** curriculum with **new** teachers |

DV: Reading test score of teacher's class

***Mean per group***

| | Experimental condition | |
|---|---|---|
| Experience of teachers | Old curriculum | New curriculum |
| Experienced teachers | 56 | 61 |
| New teachers | 30 | 60 |



# Within-person Designs

Also called **within-subjects designs** or within-groups designs.

This might include a pretest and posttest:

One group → Pretest → Treatment → Posttest → Treatment → Posttest 2

…or more within-person observations of the DV.

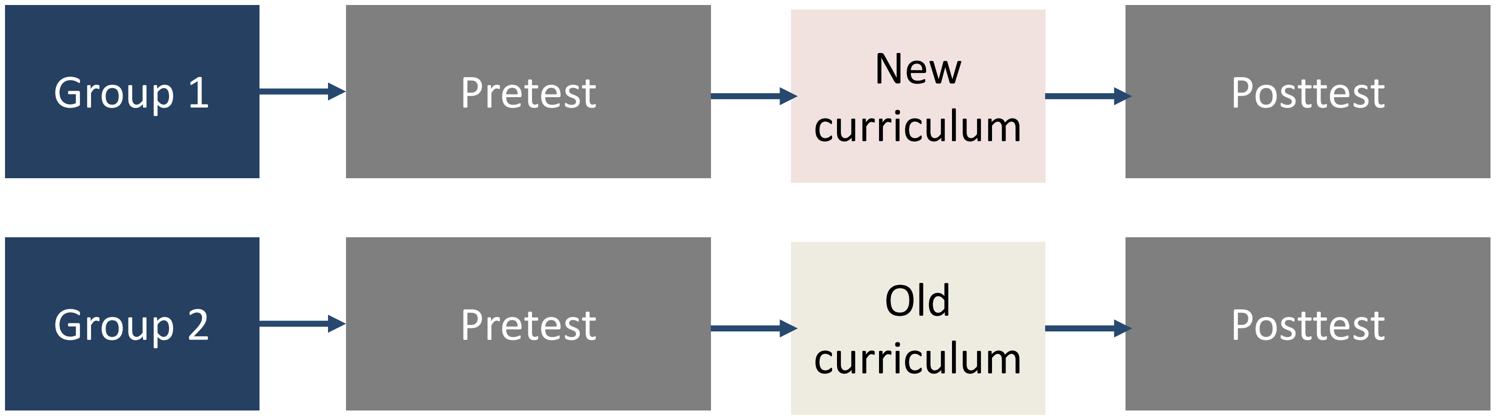
This pretest-posttest design is common in educational research:

| | | | | |
|---|---|---|---|---|
| `Treatment group` | $NR$ | $O_1$ | $X$ | $O_2$ |

*Pretest-Posttest Single-Group Design*

# Mixed Designs

These include a within- and a between-design together. In ANOVA, this is called mixed-factorial designs. This is a 2 x 2 within-between factorial design:




**This can be used for pretest-posttest group designs.**

| | | | | |
|---|---|---|---|---|
| Treatment group | $R$ | $O_1$ | $X$ | $O_2$ |
| Control group | $R$ | $O_1$ | | $O_2$ |

*Pretest-posttest equivalent groups design*

| | | | |
|---|---|---|---|
| $NR$ | $O_1$ | $X$ | $O_2$ |
| $NR$ | $O_1$ | | $O_2$ |

*Pretest-posttest **non**-equivalent groups design*

# Regression

## Simple and Multiple Regression

Simple regression:

$$Y_i = b_0 + b_1 X + \epsilon_i$$

Multiple regression:

$$Y_i = b_0 + b_1 X_1 + b_2 X_2 + \epsilon_i$$

## Example from EDUC 614: Regressing reading test scores on shoe size.

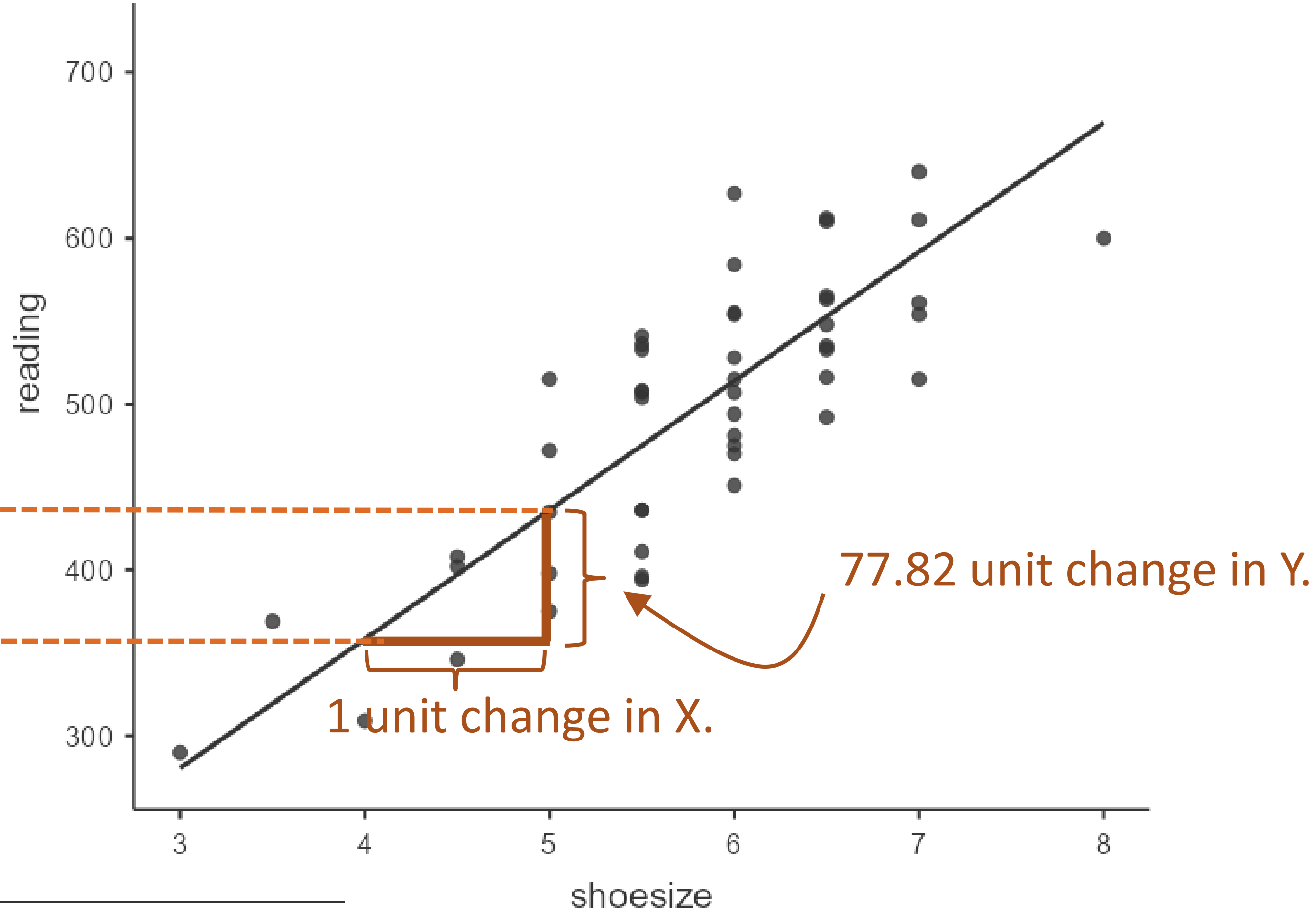
- The estimated slope parameter ($\hat{b}$) is $\hat{b} = 77.82$.

Predicted score on Y when X = 5.

$47.046 + 77.817(\mathbf{5}) = 436$

$47.046 + 77.817(\mathbf{4}) = 358$

Predicted score on Y when X = 4.




Model Coefficients - reading

| Predictor | Estimate | SE | 95% Confidence Interval Lower | 95% Confidence Interval Upper | t | p |
|---|---|---|---|---|---|---|
| Intercept | 47.046 | 43.871 | −41.162 | 135.255 | 1.072 | 0.289 |
| shoesize | 77.817 | 7.435 | 62.868 | 92.765 | 10.467 | < .001 |

**—Jamovi output—**

# Example from EDUC 614: Regressing reading test scores on shoe size.

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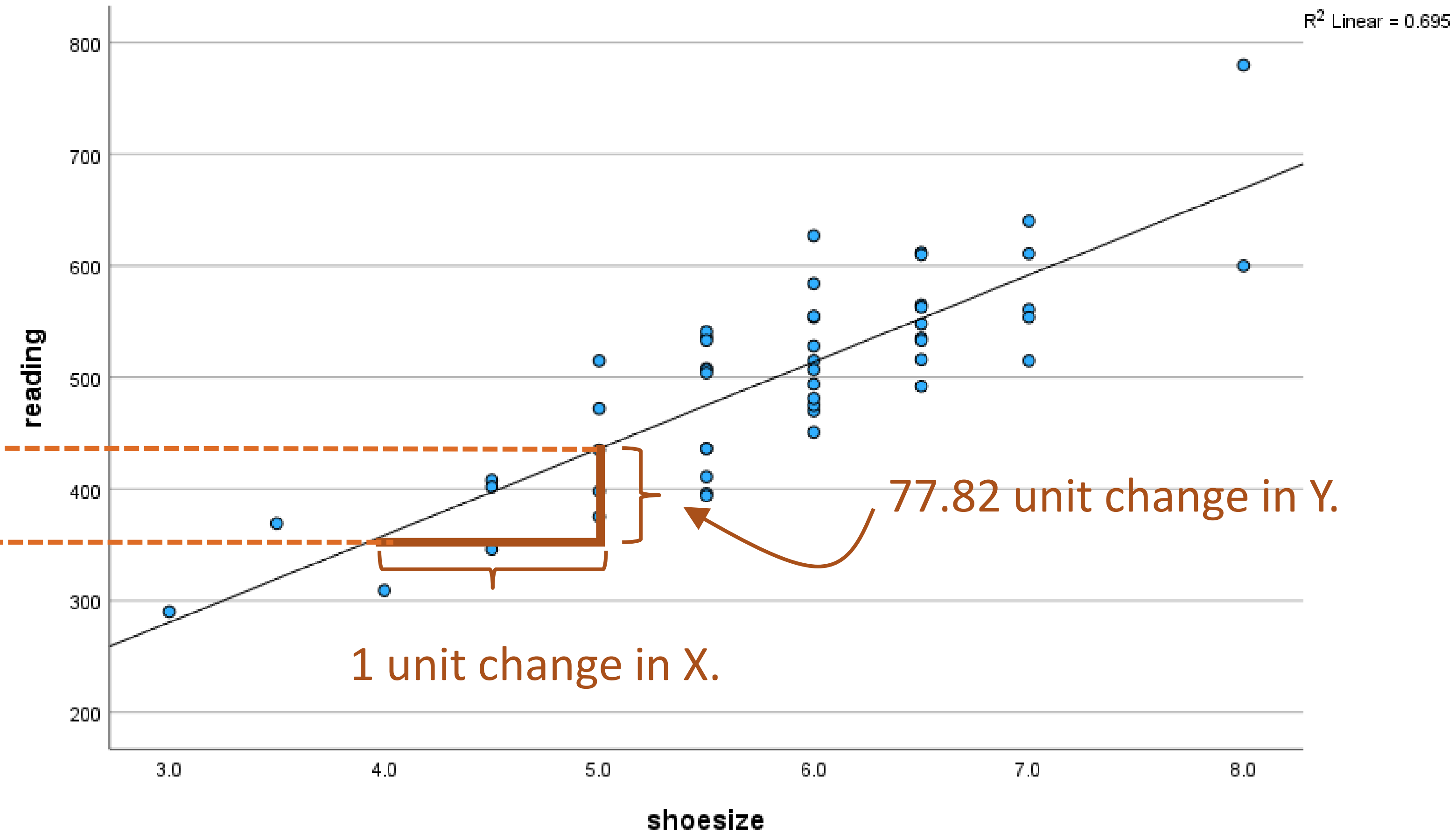



**Coefficient**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. | 95.0% Confidence Interval for B Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|---|---|
| 1 | (Constant) | 47.046 | 43.871 | | 1.072 | .289 | -41.162 | 135.255 |
| | shoesize | 77.817 | 7.435 | .834 | 10.467 | <.001 | 62.868 | 92.765 |

a. Dependent Variable: reading

—SPSS output—

# General Linear Model (GLM)

# We can also think of a *t*-test as a special case of regression:

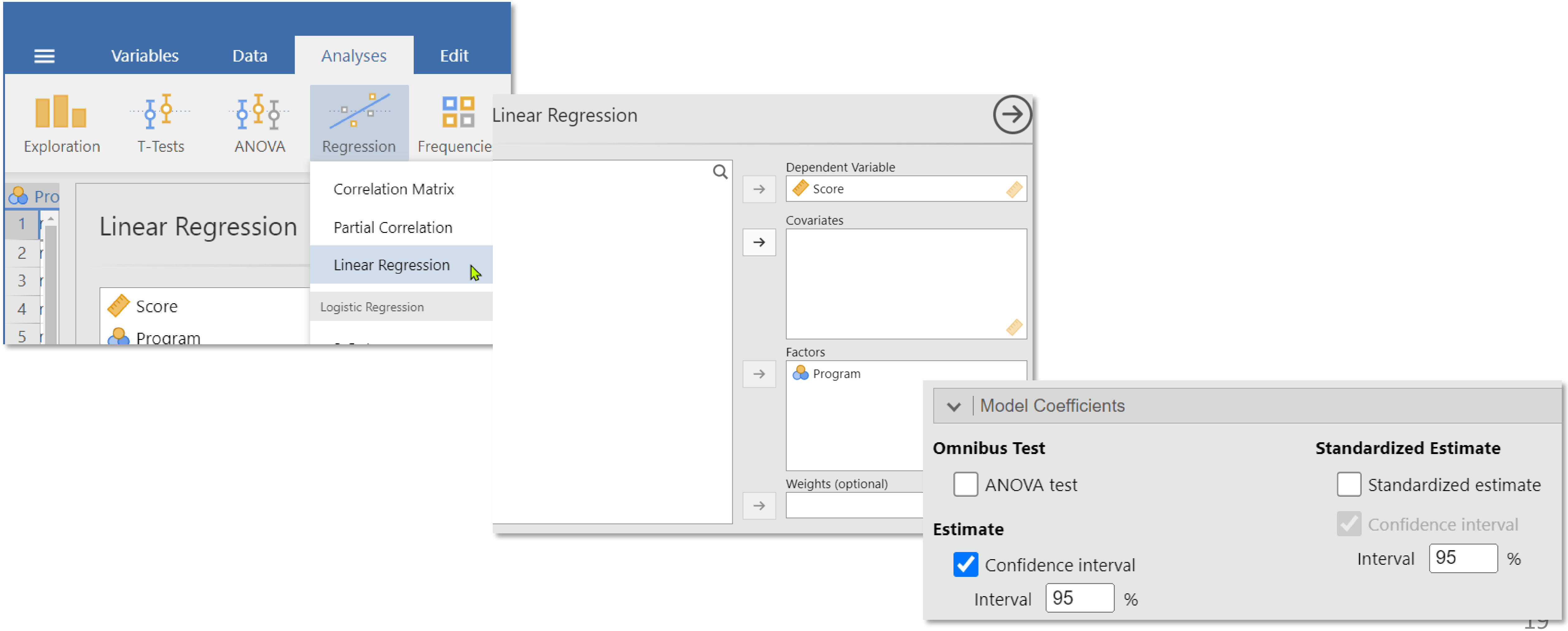
## The **general linear model** approach to a *t*-test

- Basically, we're using a more general version of regression that allows for dichotomous independent variables.
- This is because we can treat dichotomous variables as quantitative if we code them as 0 and 1.
  - This is called dummy coding.

- Why do this?
  - This becomes valuable when we want to include covariates in addition to our grouping variable.
    - For example, maybe we want to see the difference between the two groups after we have taken into account each students' earlier exam scores before they entered their respective online / on-campus program.
    - The covariate is the previous year's test scores, which we are "controlling for" (taking into account) when we examine the mean difference between the two groups.
    - A traditional *t*-test cannot do this!

# Let’s model this *t*-test as a regression (as a GLM):

Analyses → Regression → Linear Regression → enter the DV in the Dependent field and the group in the Factors field → check “Confidence interval” in the Model Coefficients drop down menu.



# Example from EDUC 614: Fitting a *t*-test as a regression (as a GLM):

Here's is the output of the *t*-test as regression:

Model Coefficients - Score

| | | | 95% Confidence Interval | | | |
|---|---|---|---|---|---|---|
| Predictor | Estimate | SE | Lower | Upper | t | p |
| Intercept [a] | 84.00 | 0.93 | 81.85 | 86.15 | 90.06 | < .001 |
| Program: | | | | | | |
| On campus – Online | 7.80 | 1.32 | 4.76 | 10.84 | 5.91 | < .001 |

[a] Represents reference level

Compare this result to the *t*-test with the same data:

Independent Samples T-Test

| | | | | | | | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | Statistic | df | p | Mean difference | SE difference | Lower | Upper |
| Score | Student's t | −5.91 | 8.00 | < .001 | −7.80 | 1.32 | −10.84 | −4.76 |

*Note.* $H_a$ $\mu_{\text{Online}} \neq \mu_{\text{On campus}}$

The benefit of the GLM is we can include covariates.

*t*-tests switch the + and − sign. 😑

The benefit of the traditional *t*-test is we can account for unequal variances (Welch's test)

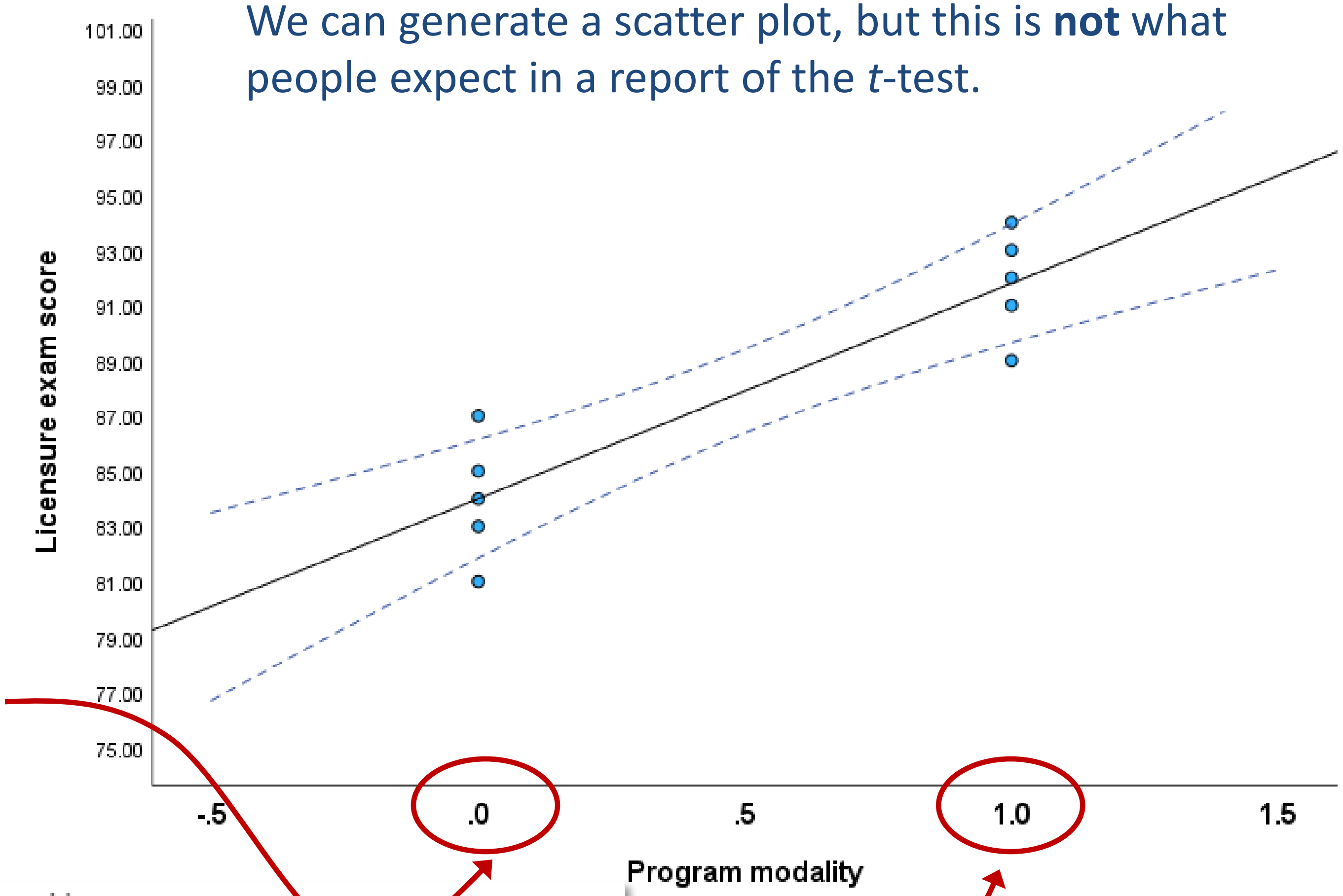
# With this way of thinking about it, we can see that the mean difference is the same as the slope.

- Here, the mean difference is the slope, $b_1$ = 7.80.

$$\begin{aligned}\hat{Y} &= b_0 + b_1 X \\ &= 84.00 + 7.80X\end{aligned}$$

- X is like a switch—it's either **0** or **1**.

We can generate a scatter plot, but this is **not** what people expect in a report of the *t*-test.

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# With this way of thinking about it, we can see that the mean difference is the same as the slope.

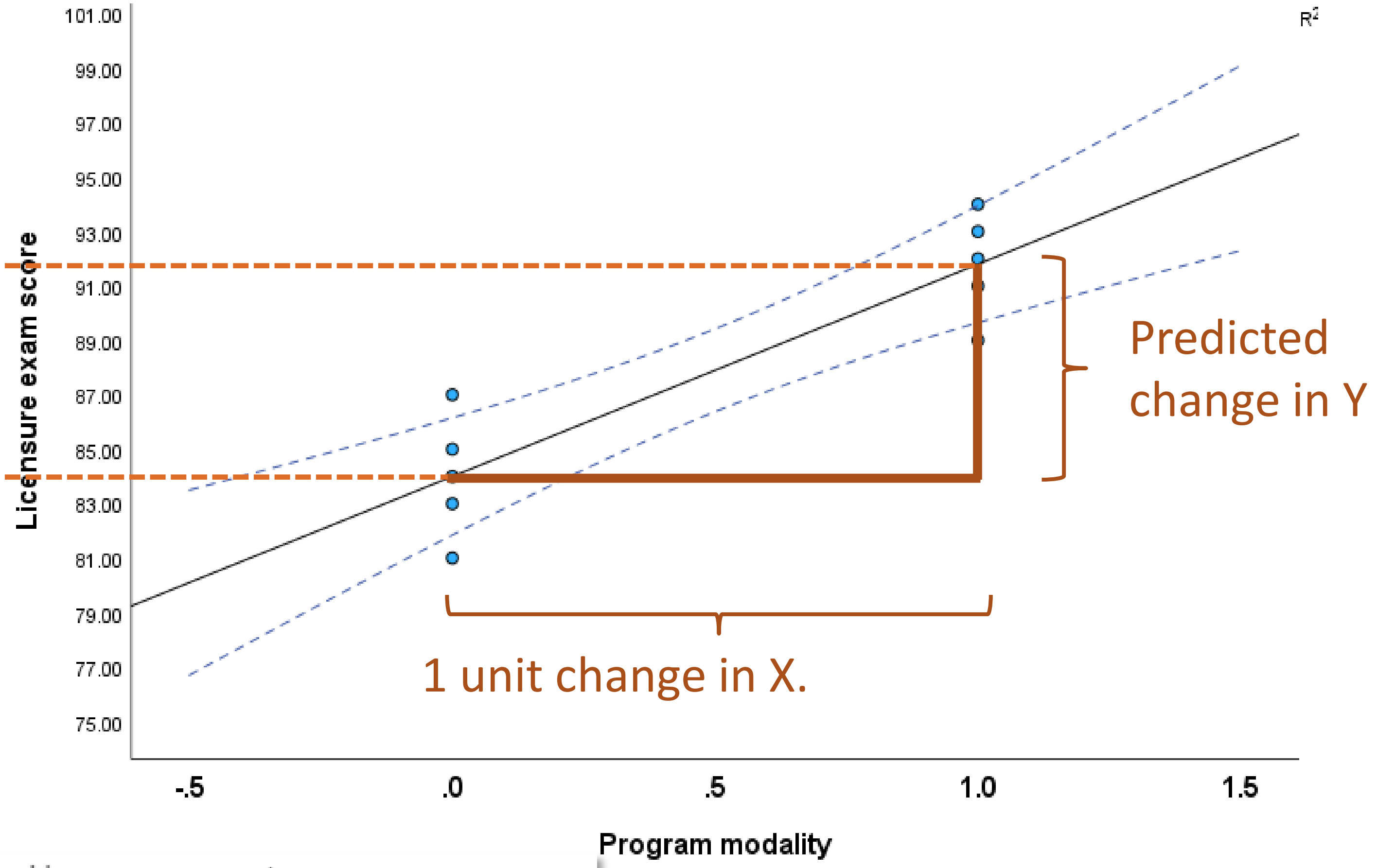
- Group 0's score is the intercept, 84.
  Group 1's score is 84 plus the slope.

$84.00 + 7.80(1) = 91.80$

Predicted score on Y when X = 1.

$84.00 + 7.80(0) = 84.00$

Predicted score on Y when X = 0.

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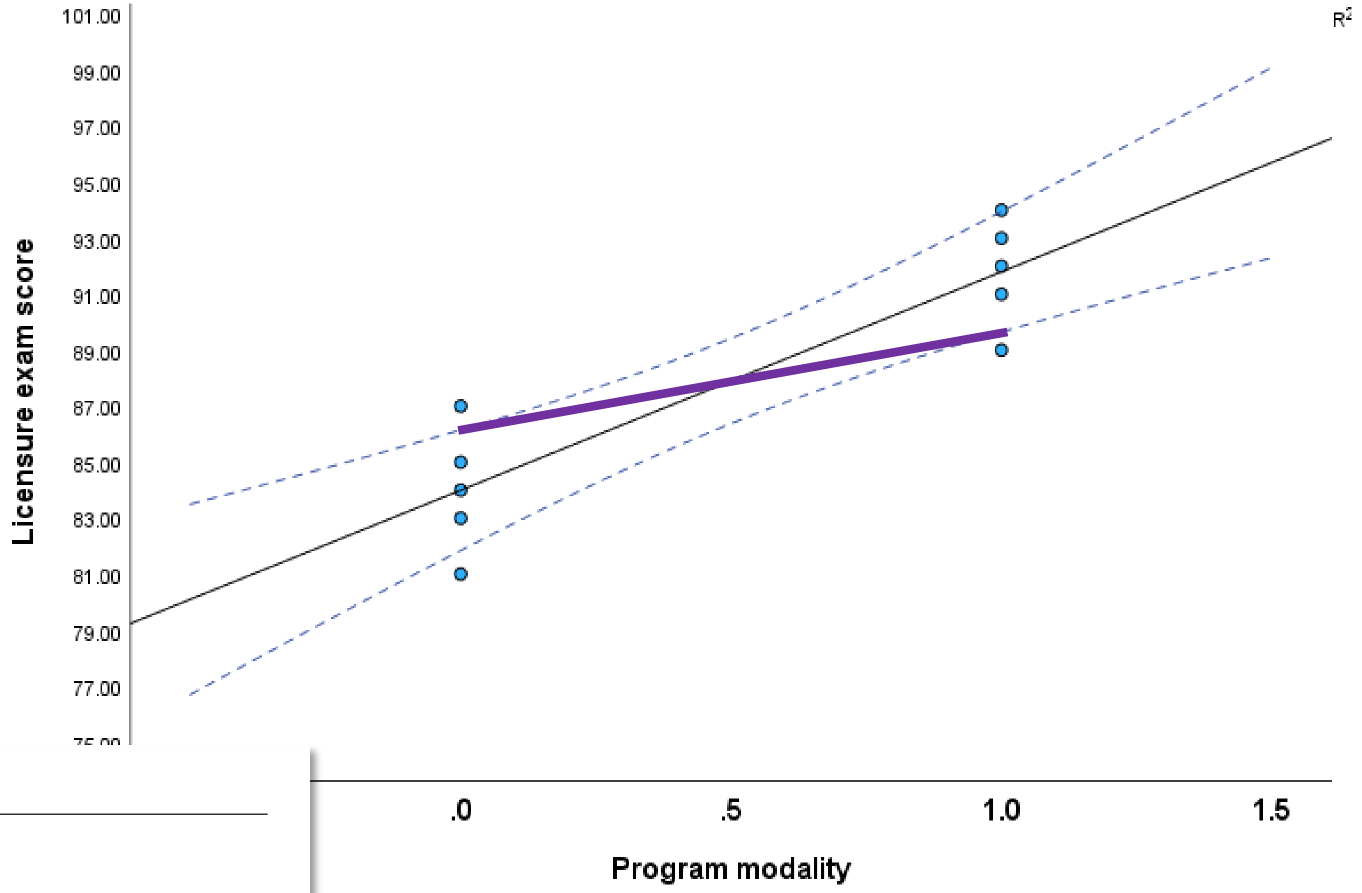
# With this way of thinking about it, we can also better understand the confidence intervals of the mean difference.

- This is the same way we looked at the confidence intervals in regression.
  - Here, we see the lower-bound of what that slope might be.

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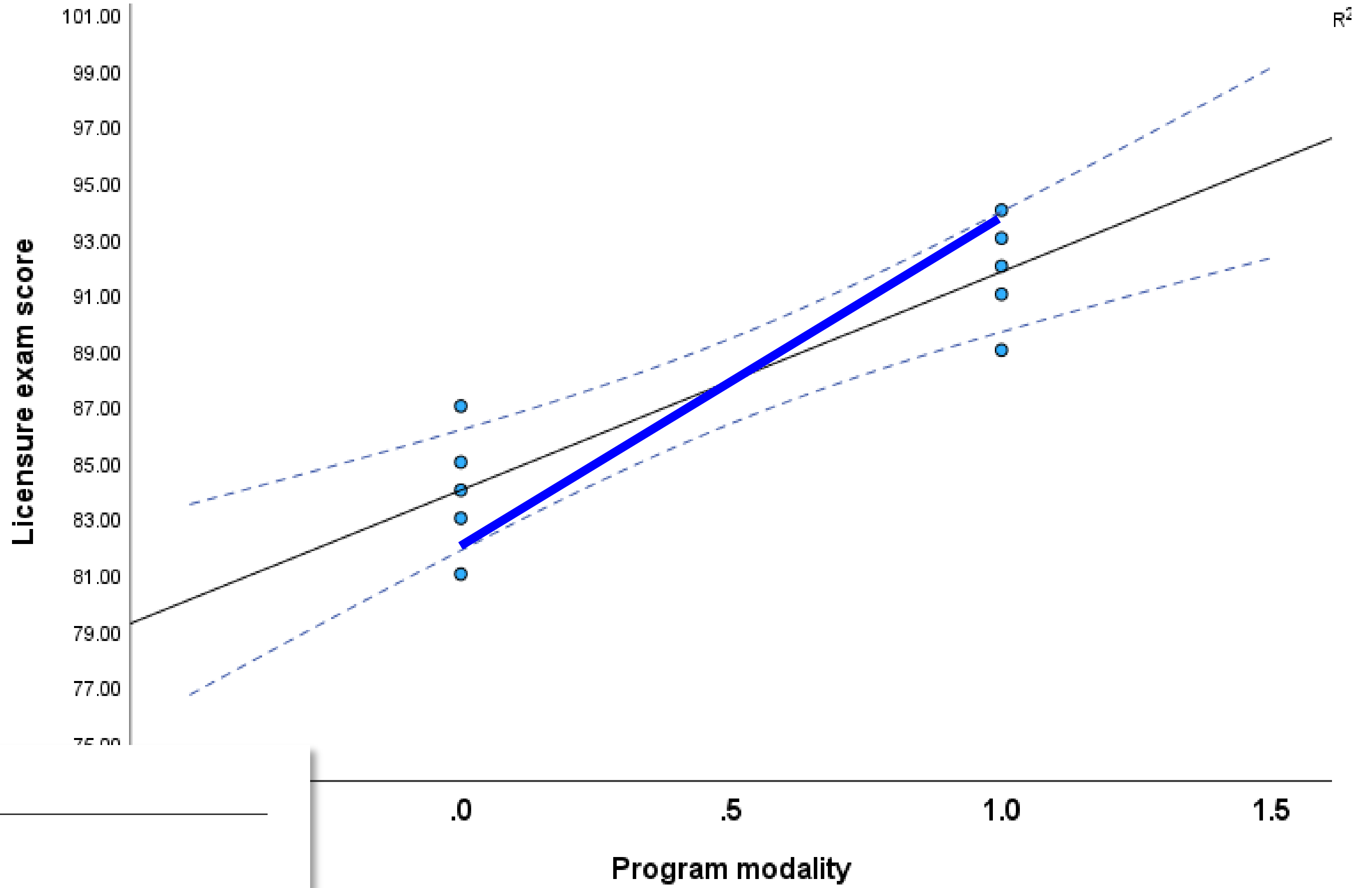
$$\hat{Y} = 86.15 + 4.76X$$

# With this way of thinking about it, we can also better understand the confidence intervals of the mean difference.

- This is the same way we looked at the confidence intervals in regression.
  - Here, we see the upper-bound of what that slope might be.
- We have 95% confidence that our sample's CI includes the population's mean difference.

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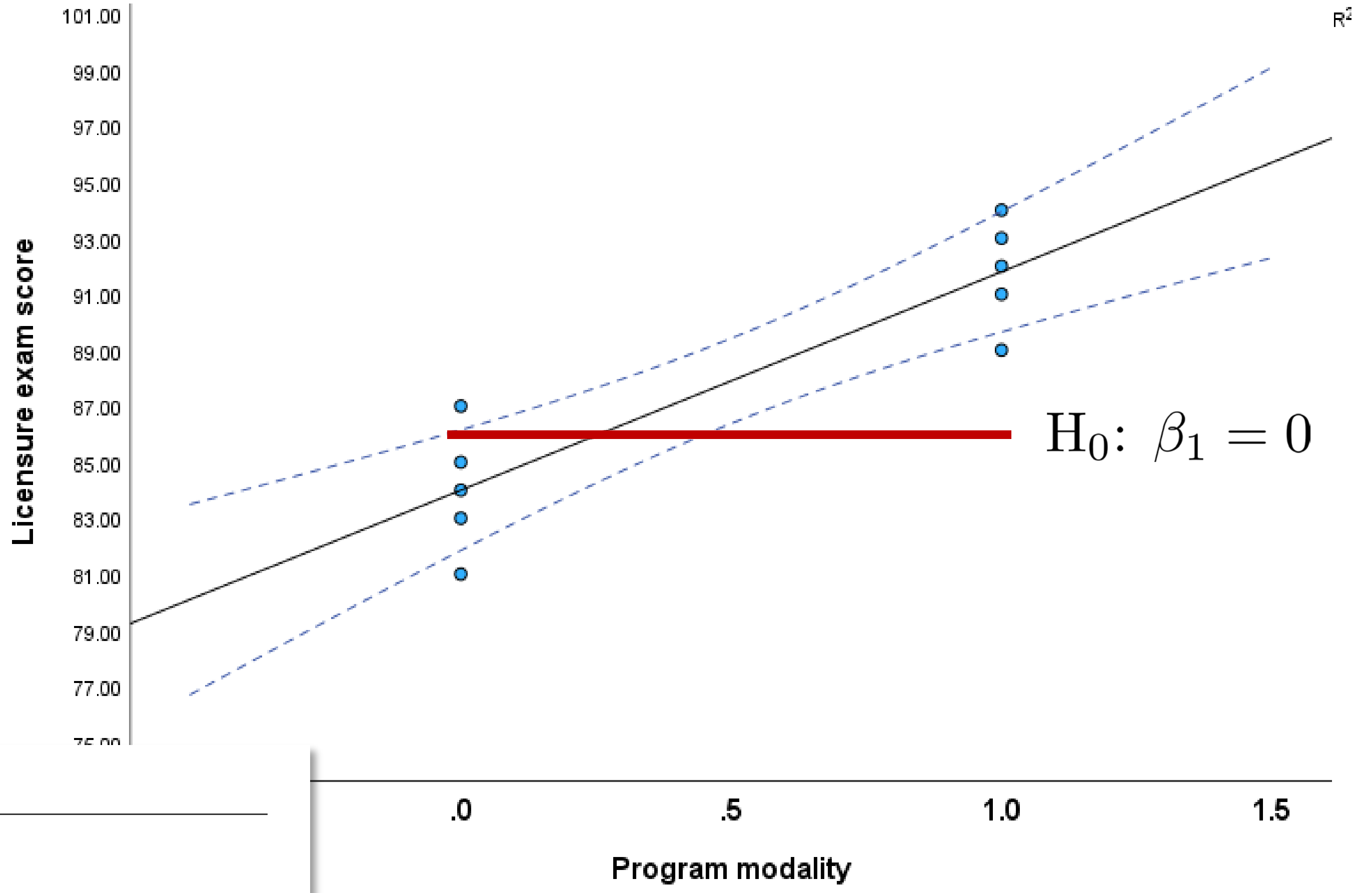
$$\hat{Y} = 81.85 + 10.84X$$

# If we superimposed a null-hypothesis line:

- The null hypothesis is that there is no difference; i.e., **0** slope.
- Is there any way we can fit a null-hypothesis slope of 0 within this confidence interval?
  - In our example, **no**. A horizontal line between X = 0 and 1 at any value of Y will result in a line that goes outside the confidence interval.
    - So, we know we can reject $H_0$.

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## ANOVA is handy when we have one or two categorical variables.

- When we're interested in analyzing group differences, ANOVA is useful.
  - But we can also use GLM.
- When we're interested in analyzing group differences while also accounting for many other variables, whether they be continuous or categorical, **GLM** is useful.
  - For example, for examining whether there are differences in children's depression levels based on whether they were in the treatment or control condition, and whether this difference depends on parents' alcohol use, amount of outdoor activity, screen time, and so forth.