Moderation and Mediation

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Moderation and mediation are extensions of the regression / general linear model (GLM) framework.

Moderation and mediation are more realistic analyses than basic regression. It's rare to simply have many predictors predict an outcome without anything more interesting going on. You might expect some IVs to interact with each other (moderation), or to have one cause another (mediation).

Alternatively, you may be interested specifically one primary relationship, and moderation and mediation can help you truly understand what is happening to that primary relationship.

Moderation and mediation are often examined in the literature. Because of their prevalence, it's critical to understand them, and to understand the differences between them.

Moderation

Moderation is another way to say that there is an interaction between predictors; a moderation effect is a standard, significant interaction.
While any interaction *could* be called moderation, there are specific circumstances where an interaction is commonly described as moderation:

- The relationship between one of the independent variables (IVs) in the interaction and the outcome variable is the primary effect of interest.
  - For clarity in today's lesson, I'll refer to the IV that is of primary interest as the **predictor** even though they are both technically predictors.
- The researcher is using the other IV to describe this primary relationship more thoroughly.
  - The IV that *describes* the primary relationship is what the researcher refers to as the **moderator**.
- Usually the moderator is preexisting in the participant rather than manipulated (quasi-experimental).
  - Demographic variables are very common moderators.

Moderation is the interaction between the predictor (effect of interest) and the moderator.

Regression example:
Using the wage dataset, we're interested in seeing if age predicts wage. We also want to see if the relationship between age and wage is different for different sexes.
predictor = age
outcome = wage
moderator = sex

Table 1
Wage as Predicted by Sex, Age, and the Interaction between Sex and Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	10.124	.293		34.602	.000
	Sex	-2.256	.431	-.218	-5.229	.000
	age_c	.130	.026	.295	5.073	.000
	ageXsex	-.092	.037	-.145	-2.497	.013

a. Dependent Variable: Wage

Because we're including an interaction we want to center the variables first. This reduces any spurious multicollinearity. I did this by subtracting the mean age (36.881) from each age value. Because sex is dummy coded (0 and 1) we don't need to worry about centering them. So to create the interaction term we multiplied centered age by dummy coded sex.

Based on our output, we can see that the predicted wage for males who are 36.881 years old is $10.12.
The predicted wage for females who are 36.881 years old is $2.26 less than males ($7.86).
For males, being one year older yields a $0.13 increase in predicted wage.
What does the interaction tell us? It could be interpreted two different ways:

- The $2.26 predicted wage discrepancy for females (age 37) goes down another $0.09 for females one year older; At age 38, females are predicted to make $2.35 less than males, age 39 = $2.44 less, etc.
- The $0.13 increase in predicted wage that a one year increase in age affords you is $0.09 less for females. So female predicted wages increase $0.04 every year.

Because our primary relationship of interest is between age and wage, one of these interpretations is more appropriate:

- The relationship between age and wage is different for each sex.
- Sex is a moderator for the relationship between age and wage.
- Males receive a $0.13 increase in predicted wage for a one year increase in age, while females receive a $0.04 increase for a one year increase in age.
- You would want to write it up that "Sex moderates the relationship between age and predicted wage, such that while predicted wage increases $0.13 per year for males, it only creases $0.04 for females."

This can be mapped out easily in a graph. The difference in slopes demonstrates the moderation.

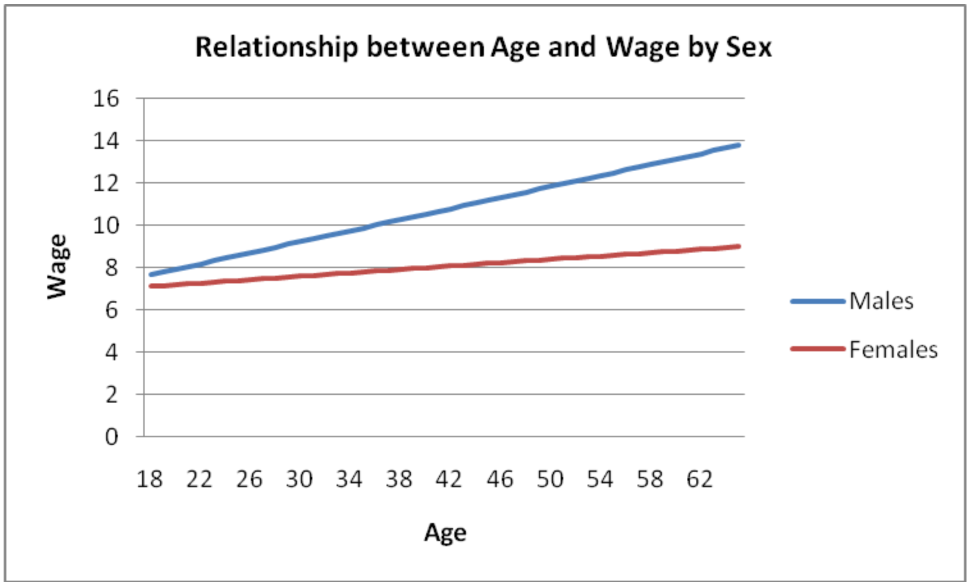


Figure 1. The Relationship between Age and Wage as Moderated by Sex

Note that the moderator (and predictor) could be continuous or categorical. It doesn't matter.
Also, we could have 2 moderators for a 3-way interaction (We could have an age/sex graph for each level of race), or more moderators than that for more complicated interactions.
Keep in mind as well, this can be examined in an ANOVA framework in addition to regression. They're both instances of the General Linear Model. For the ANOVA framework we would simply be using all categorical IVs: We'll go over an example of that now.

This dataset looks at sense of belonging among college freshmen. Sense of belonging was measured 4 times (once a month for the first 4 months of school) among college freshmen. Additionally, data was collected about the types of student organizations each participant voluntarily joined (if any). This was categorized as a Greek organization, a sports organization, or no organization. The main effect of interest is how sense of belonging changes over time. However, we think this relationship might be different for each organization type.

Outcome: sense of belonging
Predictor: time (in months) **(within-subjects)**
Moderator: student organization membership **(between-subjects)**

Output can be seen on the next page.

Table 2
Sense of Belonging as Predicted by Student Organization Membership

Tests of Between-Subjects Effects

Measure: belong
Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	15336.750	1	15336.750	456.866	.000
org	414.125	2	207.062	6.168	.021
Error	302.125	9	33.569		

Table 3
Sense of Belonging as Predicted by Time and the Interaction between Time and Org

Tests of Within-Subjects Effects

Measure: belong

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	1152.417	3	384.139	114.763	.000
	Greenhouse-Geisser	1152.417	2.489	462.945	114.763	.000
	Huynh-Feldt	1152.417	3.000	384.139	114.763	.000
	Lower-bound	1152.417	1.000	1152.417	114.763	.000
time * org	Sphericity Assumed	130.208	6	21.701	6.483	.000
	Greenhouse-Geisser	130.208	4.979	26.153	6.483	.001
	Huynh-Feldt	130.208	6.000	21.701	6.483	.000
	Lower-bound	130.208	2.000	65.104	6.483	.018
Error(time)	Sphericity Assumed	90.375	27	3.347		
	Greenhouse-Geisser	90.375	22.404	4.034		
	Huynh-Feldt	90.375	27.000	3.347		
	Lower-bound	90.375	9.000	10.042		

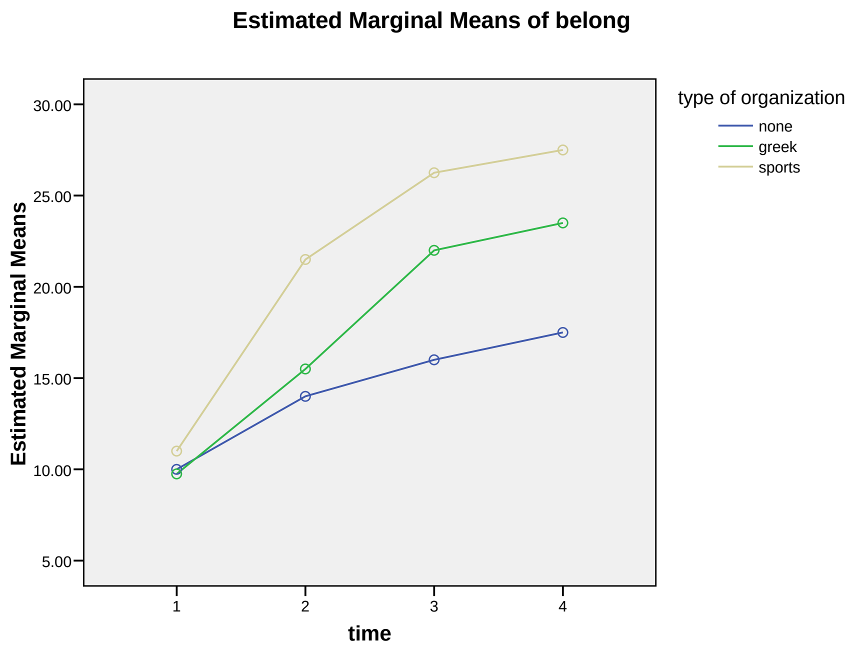


Figure 2. Sense of Belonging across Time Moderated by Organization Membership

Again, notice that the moderators are ones that are not affected by the experiment.
We just want to determine over what pre-existing groups would our experimental, intervention effect differ, which is an interaction effect.
This enhances our understanding of our primary effect, the intervention.
Predictors do not need to be manipulated, but often are. In both of our examples, the predictors (age and time) are naturally occurring.

Does the primary effect have to be significant in order to test for moderation? NO.
Moderation does not necessarily imply that the effect of interest has to be significant. Interactions do not require the main effects to be significant.

Mediation

Mediation is a theory regarding **how** the primary relationship operates.

Tests of mediation can be done sequentially using multiple regression, or can be done simultaneously if path analysis (a type of Structural Equation Modeling (SEM)) is used.

- If testing multiple mediators at the same time, SEM used to be required. Now there are special macros developed for SPSS that allow this. See Preacher and Hayes (2008).
- Today we will cover only the regression method, as SEM is beyond the scope of this handout.

Mediation refers to a theorized relationship among variables.

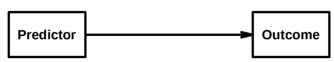
Often the predictor is experimentally manipulated, so mediators are variables that should change as a result of our experimental manipulation. Something static such as sex or race can't really be affected by the predictor, so they wouldn't be good mediators.

Mediators, like the outcome variable, are affected by the predictor, but are theorized to be one agent of change on the outcome variable.

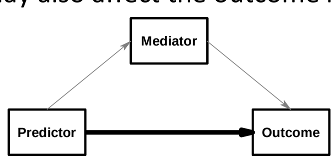
Note: If you are manipulating your predictor, you should allow for that predictor to affect the mediator, and for that mediator to affect the outcomes. Often this necessitates at least 3 waves of data. However, mediation analyses are routinely performed on cross-sectional data, especially if the predictor is categorical because no pre-test data is taken.

Before we proceed, we'll review some terminology that it's necessary we understand:

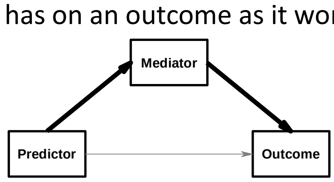
Total effect = the relationship between your predictor of interest and your outcome measure, ignoring all other variables.



Direct effect = the relationship between your predictor of interest and your outcome measure, after controlling for other variable(s) that may also affect the outcome measure.



Indirect effect = the effect a predictor has on an outcome as it works through a mediator.

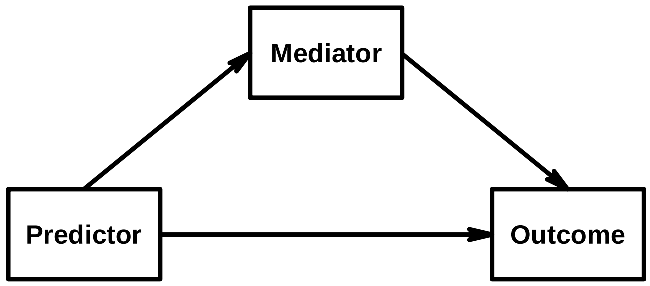


Total effect = direct effect + indirect effect

Ultimately, mediation is a test of an indirect effect; Mediation = significant indirect effect

Full mediation implies that the direct effect is not statistically different from 0 (obviously the indirect is). In other words, the mediator is the whole reason for the relationship between the predictor and the outcome.

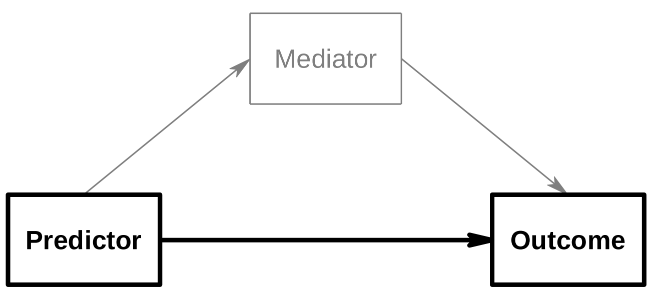
Partial mediation implies that both the direct and indirect effects are different from 0. So the mediator is definitely affecting the relationship, as demonstrated by the significant indirect effect, but the predictor still has some influence on its own, as demonstrated by the significant direct effect.



Mediation Steps (via Baron & Kenny)

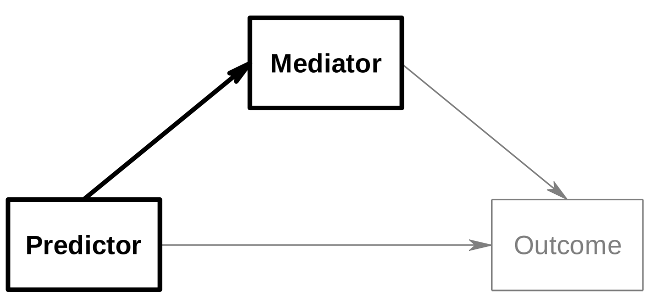
1. First we establish the effect of interest (total effect); no significant total effect *usually* means no significant direct or indirect (not always; we'll see an example of that later).
2. Then we establish a relationship between the IV and the mediator (half of indirect effect)
3. Then we establish a relationship between mediator and DV (other half of indirect)

Step 1: Total Effect



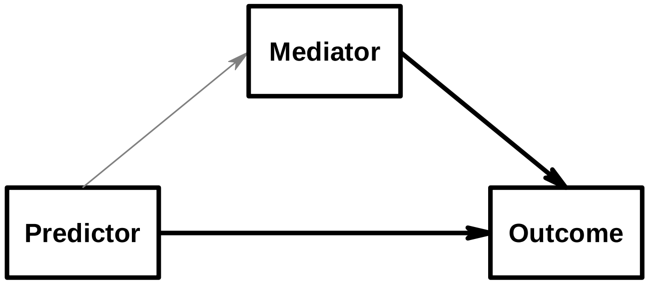
Total Effect

Step 2: IV & Mediator



First half of indirect effect

Step 3: Mediator & DV



Note that the IV has to be included in this step. Why?
By entering both the predictor and the mediator into the regression simultaneously, you will assess only their *unique* prediction on the outcome variable. You're controlling for the predictor while assessing the mediator's effect and vice versa. This provides the direct effect AND the second half of the indirect effect.

1st example:
Using the wage dataset again, we wanted to see if the relationship between education and wage was mediated by the amount of experience participants have.
predictor = education
outcome = wage
mediator = experience

This is a reasonable mediator, because experience could be affected by the education of the participant; It is not unchangeable over time like most demographic variables are.

Step 1

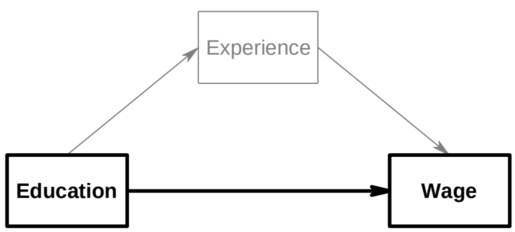


Table 4
Wage as Predicted by Education

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.696	1.058		-.658	.511
	Education	.747	.080	.379	9.394	.000

a. Dependent Variable: Wage

Step 2

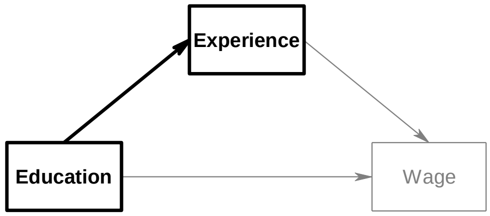


Table 5
Experience as Predicted by Education

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	39.597	2.566		15.429	.000
	Education	-1.668	.193	-.353	-8.643	.000

a. Dependent Variable: Experience

Step 3

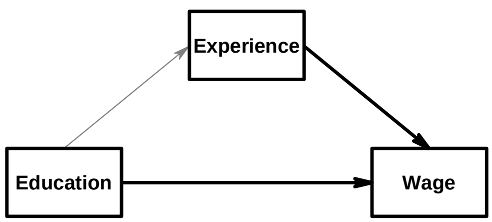


Table 6
Wage as Predicted by Education and Experience

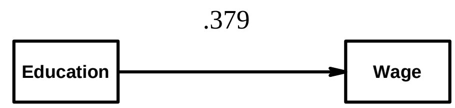
Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-4.893	1.233		-3.968	.000
	Education	.924	.082	.469	11.237	.000
	Experience	.106	.017	.254	6.097	.000

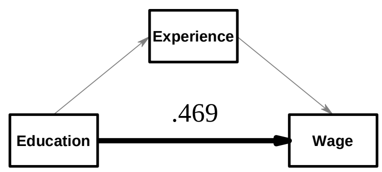
a. Dependent Variable: Wage

All values reported below are betas.

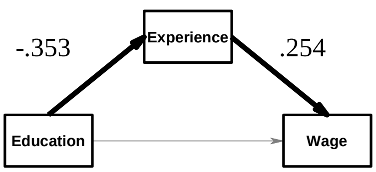
Total effect:



Direct effect:



Indirect effect:



Total effect = direct effect + indirect effect
.379 = .469 + (-.353)(.254)
.379 = .469 - .090
.379 = .379

2nd example:
Using the wage dataset again, we wanted to see if the relationship between experience and wage was mediated by the amount of leadership participants have in their job roles. So higher leadership scores indicate that the participant has more of a leadership role in the organization.
predictor = experience
outcome = wage
mediator = leadership

This is a reasonable mediator, because leadership could be affected by experience of the participant; It is not unchangeable over time like most demographic variables are.

Step 1:

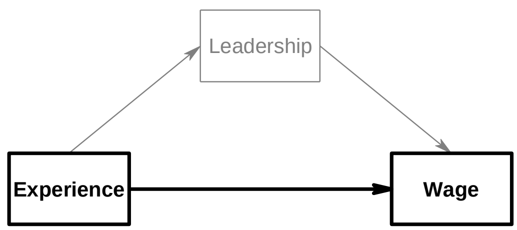


Table 7
Wage as Predicted by Experience

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.386	.393		21.344	.000
	Experience	.037	.018	.089	2.049	.041

a. Dependent Variable: Wage

Step 2:

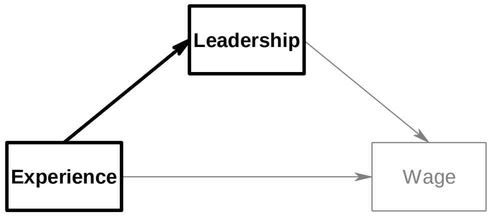


Table 8

Leadership as Predicted by Experience

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	20.349	.187		108.626	.000
	Experience	.926	.009	.978	107.319	.000

a. Dependent Variable: Leadership

Step 3:

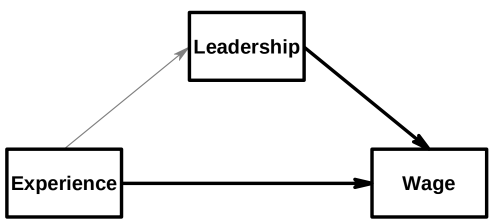


Table 9

Wage as Predicted by Experience and Leadership

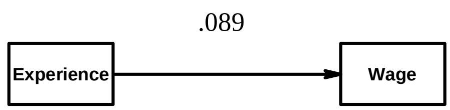
Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-10.357	1.710		-6.055	.000
	Experience	-.816	.078	-1.958	-10.476	.000
	Leadership	.921	.082	2.093	11.200	.000

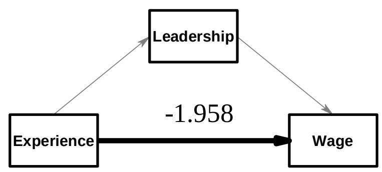
a. Dependent Variable: Wage

All values reported below are betas.

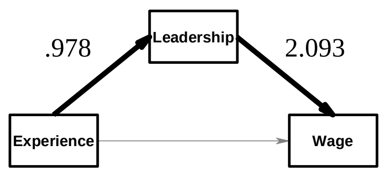
Total effect:



Direct effect:



Indirect effect:



Total effect = direct effect + indirect effect
.089 = -1.958 + (.978)(2.093)
.089 = -1.958 + 2.047
.089 = .089

Note that the total effect (predictor alone) was .089 and the predictor effect (direct) after the mediator was included was -1.958.
.089 – (-1.958) = 2.047
Note that the two pieces of the indirect effect were predictor → mediator (.978) and mediator → outcome (2.093).
.978*2.093 = 2.047

What other effect do we see here?
Suppression.
The total effect and direct effect have opposite signs.

How is this possible? The indirect effect is greater than the total effect. The indirect effect is suppressing the relationship between the predictor and outcome.

How do you interpret this?

- After controlling for leadership, experience actually has a negative influence on wage, such that having more experience predicts lower wages.
- However, having more experience is usually associated with job roles with more leadership, and leaders have a higher predicted wage. This effect is so strong that it masks the negative relationship between experience and wage (or suppresses it).

So we would report this as mediation with a suppression effect, *not* partial mediation.

Testing the Indirect Effect:

As with most other analyses, we can do a significance test to see if the change in the relationship between the predictor and the outcome is significant (i.e. if the indirect effect is significant).
If there is not a significant indirect effect, then the relationship between the predictor and the outcome will not be affected by including a mediator.
How do you test?
There are multiple possible tests you could use, but most common test is called the Sobel test, which is illustrated on many websites. My favorite is:
http://people.ku.edu/~preacher/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:	*p*-value:
a	.926	Sobel test:	11.16537733	0
b	.921	Aroian test:	11.16485622	0
s_a	.009	Goodman test:	11.16589851	0
s_b	.082	Reset all	Calculate	

Alternatively, you can insert t_a and t_b into the cells below, where t_a and t_b are the *t*-test statistics for the difference between the *a* and *b* coefficients and zero. Results should be identical to the first test, except for error due to rounding.

	Input:		Test statistic:	*p*-value:
t_a	107.319	Sobel test:	11.13950202	0
t_b	11.200	Aroian test:	11.13902366	0
		Goodman test:	11.13998044	0
		Reset all	Calculate	

This method is still being published in many journals. However, this method of significance testing is becoming outdated for a variety of reasons. See my handout regarding Indirect Effect Significance Testing for a more appropriate and modern way to test this effect.

Moderation versus Mediation
Moderation looks at **how the primary relationship is <u>different</u>** for different levels (or ranges) of another IV. The relationship between the predictor and outcome depends upon a participant's group or score for the moderator.
Mediation looks at **how the primary relationship <u>works</u>** (causal). The relationship between the predictor and the outcome is due to the fact that the predictor affects the mediator, and the mediator affects the outcome.

Compare
Both mediators and moderators attempt to augment our understanding of a specific effect.
Both mediators and moderators can be either categorical or continuous.
Both mediators and moderators can be tested with standard multiple regression / GLM techniques.
Contrast
Moderators are typically a preexisting variable or remain constant throughout the experiment, whereas mediators are affected by the experiment; **Mediators specify a causal link.**
Moderators can be tested simultaneously; Mediation in MR has to be tested with a sequence of steps.