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Email: jkanglim@unimelb.edu.au
Office: Room 1110 Redmond Barry Building
Website: http://jeromyanglim.googlepages.com/

Appointments: For appointments regarding course or with the application of statistics to your thesis, just send me an email

Moderators & Mediators

325-711 Research Methods

2007

Lecturer: Jeromy Anglim

In our workshop we will initially discuss the conceptual distinction between mediators and moderators. We will then talk about mediation in more detail, including the types of mediation, statistical techniques for testing mediation and the underlying assumptions. We will move on to a discussion of moderators, including the types of moderators, statistical techniques for testing moderators, and interpretation of main term and interaction term coefficients. Students attending this workshop are expected to have a basic understanding of multiple regression.

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Assorted Readings

- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51, 6, 1173-1182.
- Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderator effects of categorical variables using multiple regression: A 30-year review. Journal of Applied Psychology, 90(1), 94-107.
- McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. Psychological Bulletin, 114, 2, 376-390.
- Frazier, P. A., Tix, A. P., Barron, K. E. (2004). Testing moderator and mediator effects in counseling psychology research. *Journal of Counseling Psychology, 51*, 115-134.
- Howell, D. (2007). "Chapter 15: Multiple Regression (main focus is section:15.13)" in *Statistical Methods for Psychology* (6th Ed), Thomson, Australia.

Barr on & Kenny (1986) One of the most cited articles of all time in the social sciences (i.e., 7826 citations according to Google Scholar – Aug 2007). This paper sets out the distinction between mediators and moderators and provides a number of examples of each and suggestions for testing them.

Frazier, Tix, Barron (2004) This article gives a particularly clear explanation of how to test for moderation or mediation and shows how to report either analysis. If you do not have a strong background in statistics, this may be a good article to start with.
Aguinis, Beaty, Boik & Pierce (2005) This article cites many examples of moderator effects where the moderator is a categorical variable (e.g., gender, race, etc) that have been explored in the organisational behaviour literature. It notes that the effect size of moderator effects tends to be small. It also mentions rules of thumb for getting adequate power to test interaction effects.
McClelland & Judd (1993) This article discusses reasons why moderator effects tend to be so small in field settings whereas they tend to be fairly reliably found in experimental settings. This includes: field studies are less controlled; greater error of measurement tends to occur in field studies.
Howell (2007): In Howell's chapter on multiple regression, a few pages are devoted to testing mediation and moderation.

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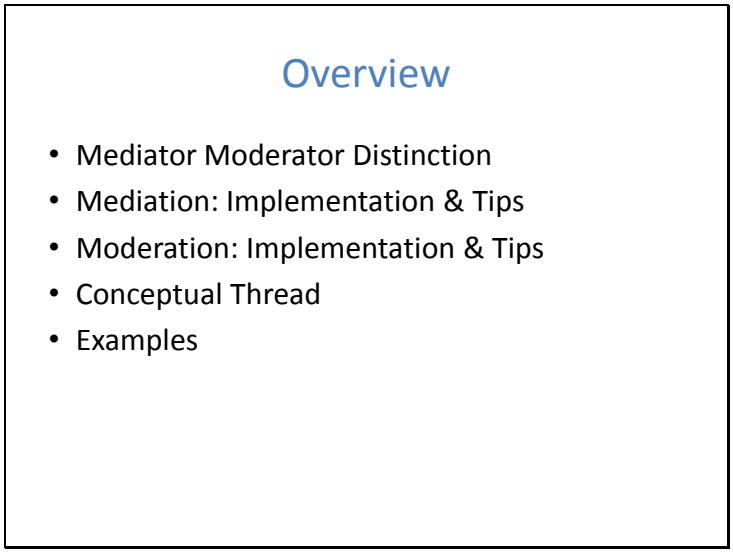

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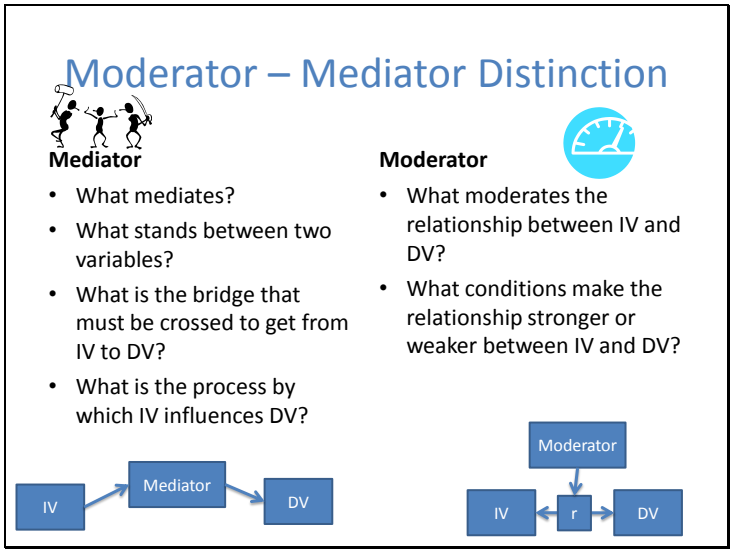

Perhaps because they both start with “m”, end with “or” and have some “d”s and “a”s inside; Perhaps because they both have everyday meanings distinct from their social science statistical meanings; Perhaps because intuition and statistics are not always aligned; perhaps because of all these reasons and more, the moderator-mediator distinction is one that is often confused.

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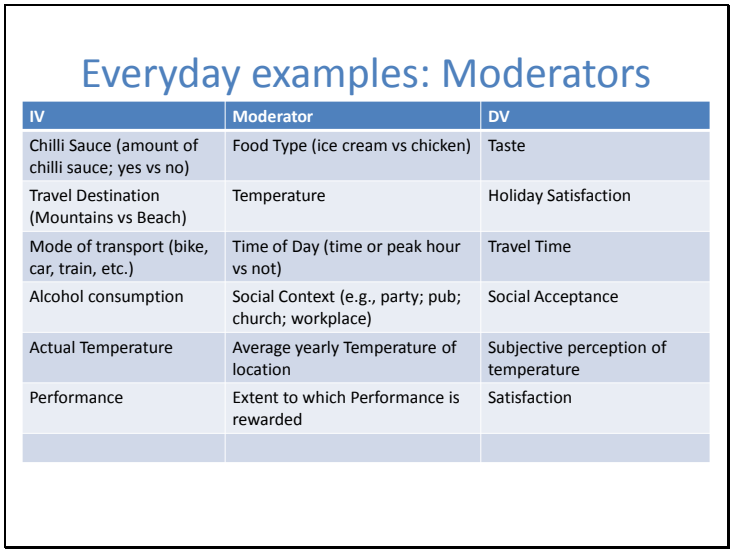

A really powerful technique for learning statistical ideas is to brainstorm many everyday examples of the idea. This can highlight how much we intuitively already see the world in terms of statistical models, such as moderation and mediation. A similar strategy is to try to explain the statistical analyses you have recently been performing to someone who knows nothing about statistics. The aim is to keep them interested, without excessively simplifying or distorting what you are doing.

What is the moderation effect present in the examples above?

I love **chilli sauce**. I think it makes chicken taste a lot better. However, I don't think it would be too good on ice cream. Thus, the effect of chilli sauce on taste is moderated by the type of food.
Certain **travel destinations** may be more or less popular. Certain temperatures are also more or less popular. If you go to a particular location these factors tend to influence people's holiday satisfaction. However, the effect of temperature is likely to be different depending on whether we are going on a skiing holiday or a beach holiday. If we were going on a skiing holiday 30 degrees Celsius would be a problem. If we were lying down on a beach, it would be great. Temperature moderates the effect travel destination on holiday satisfaction.

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Everyday examples: Mediators

IV	Mediator	DV
I kick the ball	It flies through the air	I score a goal
Hunger	Eating 30 minutes later	Satiation 1 hour later
Extraverted personality	Greater Socialising	More Friends
Education	Better Paying Job	More Expensive House
Brushing teeth	Nicer Breath	Partner more willing to kiss
Positive Attitude towards Red Hot Chilli Peppers	Buy Concert ticket to Red Hot Chilli Peppers	Go to concert of Red Hot Chilli Peppers
Attitude & Subjective Norms	Behavioural Intention	Behaviour
Skills and ability	Performance	Promotion
Wide social networks	Hearing about more job opportunities	Better Job
Happiness Yesterday	Happiness Today	Happiness Tomorrow

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Theory Building

- For every statistical technique, there is:
  - A model for interpreting the world
  - A language for clarifying thought
- The research question & the nature of the data drive the choice of statistical technique
  - But sometimes it works the other way
- Think about Statistical Techniques and how they change perceptions of the world:
  - Multiple regression; correlation; mean; standard deviation; factor analysis; ANOVA; etc.
  - What about mediation and moderation?

Every statistical technique provides a way of representing the world. One of the great joys of learning more about data analysis is that it brings a conceptual clarity to summarising empirical observation. Beyond actually testing moderation or mediation, having an awareness of the concepts enables researchers to speak clearly about these forms of

relationships and conceptualise and theorise about the world using these models. Data analytic techniques raise questions that researchers might not have otherwise thought to ask.

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Mediation:

Recipe for asking mediation-type questions

- Take 2 variables, one (IV) of which you believe causes the other (DV)
- How do you think this process operates?
- What are all the intervening stages?
- What variables get modified in the intervening stages?
- How could we empirically assess whether the proposed intervening stages were the actual intervening stages?

For example: Take Intelligence and Job Performance. If we assume that the effect is causal, we could try to brainstorm a series of potential mediators, such as: education, task specific skills, learning from training, etc.
This is a is useful exercise to go through when developing a more sophisticated representation of the variables in a particular domain.

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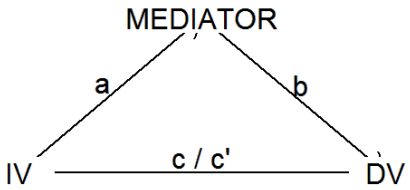
Mediation

- Direct Effect
- Indirect Effect
- Total Effect



The triangle shown above is the diagram typically shown to represent the most simple form of mediation: one IV, one mediator, and one DV. The letters a through c represent regression coefficients. These are often presented in standardised form to make interpretation clearer. The difference between c and c' is that c refers to the regression coefficient when IV predicts

DV on its own, whereas c' refers to the regression coefficient of IV on DV when MEDIATOR is also a predictor in the regression equation.
Direct Effect (c'): Effect of IV on DV after controlling for the mediator
Indirect Effect(a*b): Effect of IV on DV that occurs through the mediator. It is calculated as the IV-MV regression coefficient multiplied by the MV-DV regression coefficient
Total Effect: The sum of direct and indirect effects
When there is mediation, there is an indirect effect. When there is an indirect effect, c is less than c'.

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Why many people's tests of **mediation** are misguided

- Correlation does not mean causation
- Alternative causal pathways tend to be just as theoretically plausible as the mediational pathway proposed
  - E.g., reciprocation, a third variable (particularly an underlying trait)

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The importance of thinking

- So, you have some variables
- Why would IV lead to MV lead to DV?
- What about?
  - MV leads to IV leads to DV
  - DV leads to MV leads to IV
  - IV and MV both just predict DV
  - IV and MV are both manifestations of a 3rd variable which predicts DV
  - IV, MV and DV are reflections of an underlying factor, plus some unique bit
- 1. IV causes DV?
- 2. Mediators actually mediates?

1. Why do you think the IV causes the DV?
Once again, we need to consider our own research and the research of others. What kinds of research designs have been used and what forms of causal inference do they permit? Remember experimental designs tend to permit the strongest inferences followed by quasi-experimental (i.e., repeated measures experiments or experiments on pre-existing

groups) followed by correlational designs. In addition, using logic, reason and common sense can be helpful. Think about the different possible explanations for the relationship between the IV and the DV. Evaluate each explanation in terms of the prior research, your own research and common sense. Without acknowledging plausible alternatives, mediation analyses can be quite misleading. We should resist the albeit seductive temptation to draw causal inferences when the data is inconclusive.

2. Why do we think the causal effect of the DV is mediated by the MV?

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The Manual Regression Process

- 1. Run Regression IV predicting DV
- 2. Run Regression IV predicting MV
- 3. Run Regression IV and MV predicting DV
- 4. Run Significance test on reduction of IV-DV regression coefficient after the inclusion of the MV

- Note: There are several ways to test for mediation, including structural equation modelling

Going through the manual process of testing for mediation is a good way to learn how it works. Once you understand what is going on, it is generally quicker and more reliable to use the macros: http://www.comm.ohio-state.edu/ahayes/sobel.htm

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Example

- Research Question:
  - Is the effect of age on performance on a text-editing task mediated by typing speed?
- Variables
  - All variables are metric

Doing it the manual way, it is important to check that you have a consistent sample size for all analyses. In the present example, I had missing data on task performance, which meant that the sample size for the regression of age on typing speed had about 15 more people than the other regression. I had to apply a filter in order to only include cases that had data on all three variables.

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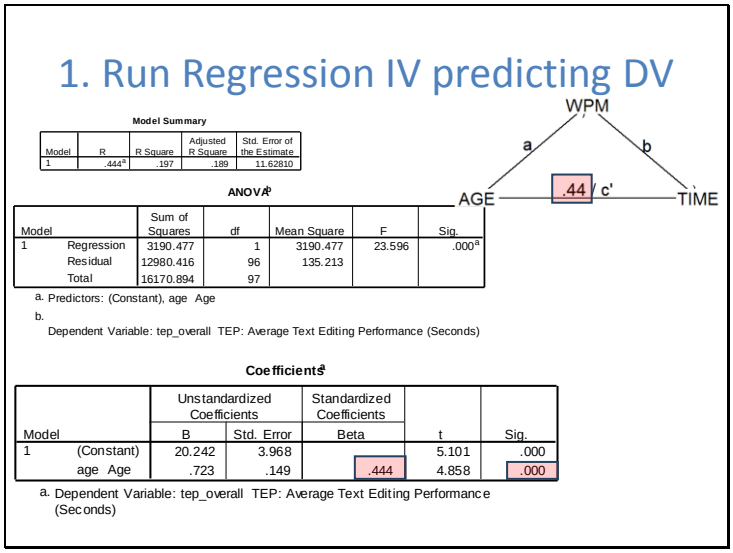

REGRESSION /STATISTICS COEFF OUTS R ANOVA /DEPENDENT tep_overall /METHOD=ENTER age.

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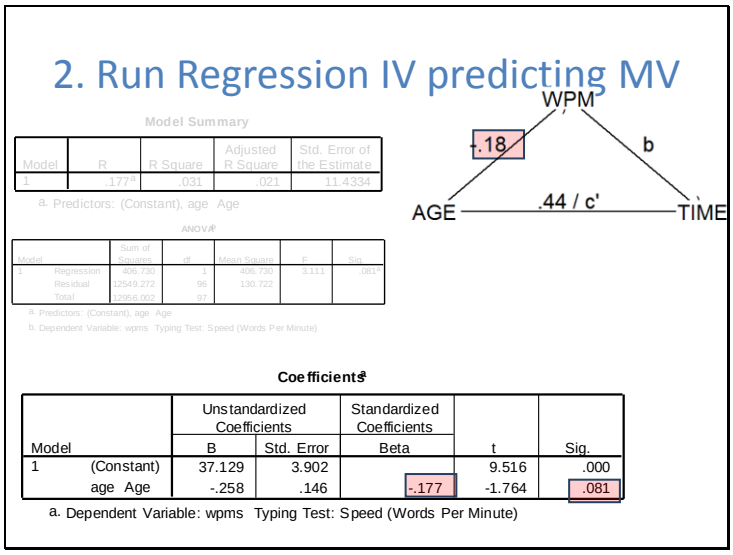

REGRESSION /STATISTICS COEFF OUTS R ANOVA /DEPENDENT wpms /METHOD=ENTER age.

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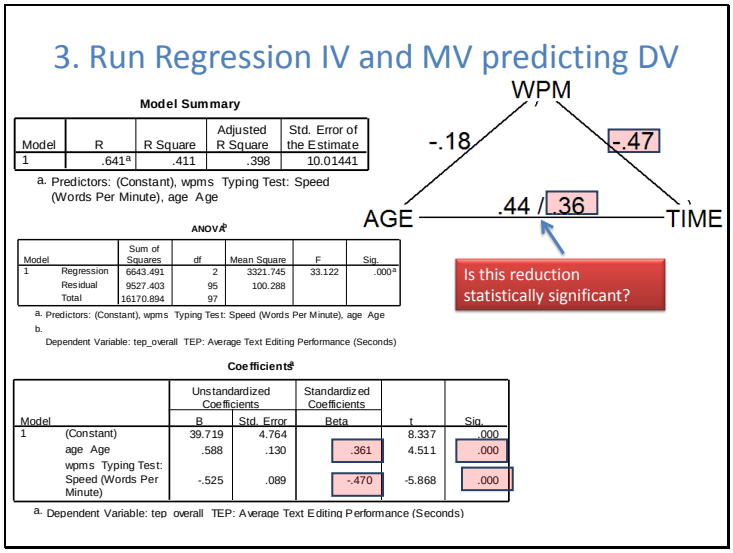

After controlling for words per minute, the effect of age appears to be smaller (.44 without WPM; .36 with WPM). Thus, at the level of descriptive statistics, there is support for partial mediation. It appears to be a long way from complete mediation, suggesting that even if typing speed was one mediational pathway, it is certainly not the only one.
The next step is to determine whether there is significant partial mediation. I.e., is the reduction of .08 (.44 to .36) in the standardised beta statistically significant?

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Significance Tests

- Sobel Test
  - http://www.psych.ku.edu/preacher/sobel/sobel.htm
- Bootstrapping approaches
  - http://www.comm.ohio-state.edu/ahayes/sobel.htm

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, and Computers, 36*, 717-731.

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4. Run Significance test on reduction of IV-DV regression coefficient after the inclusion of the MV

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	37.129	3.902		9.516	.000
	age Age	-.258	.146	-.177	-1.764	.081

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	39.719	4.764		8.337	.000
	age Age	.588	.130	.361	4.511	.000
	wpms Typing Test: Speed (Words Per Minute)	-.525	.089	-.470	-5.868	.000

a. Dependent Variable: tep_overall TEP: Average Text Editing Performance (Seconds)

Online Sobel Test Calculator
http://www.psych.ku.edu/preacher/sobel/sobel.htm

Input:		Test statistic:	p-value:
t_a 1.764	Sobel test:	1.68932005	0.09115811
t_b 5.868	Aroian test:	1.66726251	0.09546222
	Goodman test:	1.71227687	0.08684566
	Reset all	Calculate	

The sobel test p-value is less than .05. Thus, we can conclude that Typing Speed is a statistically significant partial mediator of the effect of age on task performance. Another way of saying this is that there is a statistically significant indirect effect of age on task performance through typing speed.

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Macro & Bootstrapping

- Defined the Macro by running it in SPSS:
  - http://www.comm.ohio-state.edu/ahayes/sobel.htm
- Ran the Macro on my data
  - SOBEL y=tep_overall/x=age/m=wpms/boot=1000.

```
Run MATRIX procedure:

DIRECT AND TOTAL EFFECTS
           Coeff       s.e.          t   Sig(two)
b(YX)      .7232      .1489     4.8576      .0000
b(MX)     -.2582      .1464    -1.7639      .0809
b(YM.X)   -.5246      .0894    -5.8678      .0000
b(YX.M)    .5877      .1303     4.5114      .0000

INDIRECT EFFECT AND SIGNIFICANCE USING NORMAL DISTRIBUTION
           Value       s.e.  LL 95 CI  UL 95 CI          Z  Sig(two)
  Sobel     .1354      .0812     -.0238     .2947     1.6672      .0955

BOOTSTRAP RESULTS FOR INDIRECT EFFECT
            Mean       s.e.  LL 95 CI  UL 95 CI  LL 99 CI  UL 99 CI
 Effect     .1349      .0734      .0055     .2979     -.0433      .3452

SAMPLE SIZE
        98

NUMBER OF BOOTSTRAP RESAMPLES
      1000

------ END MATRIX -----
```

This macro makes it easy to run a mediation model. It gives all the regression coefficients that were presented using the manual process, although admittedly they are unstandardised regression coefficients. The bootstrap test is statistically significant if both LL95CI and UL95CI have the same sign (e.g., both positive or both negative). This indicates that zero is not a likely value and therefore we should reject the null hypothesis that the indirect effect is zero. In this case the bootstrapped effect was statistically significant at .05 whereas the Sobel Test was not statistically significant. This is not to say that the results were that different for the two approaches. The Sobel Test was only just in the non-significant territory (p=.10), and the bootstrap test was only just statistically significant (lower limit = .0055). We should also not choose an approach based on the one that happens to give the better p value. Studies

should be designed with sufficient power such that it should not matter and decisions about which significance test to use should be based on broader considerations such as perceived accuracy.

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Bootstrapping

- What is a p value?
- What does a p value mean in the context of hypothesis testing?
- Are reported p-values always accurate?
- Bootstrap approach
  - Rely on sample to estimate sampling distribution of particular parameter of interest

See http://www.uvm.edu/~dhowell/StatPages/Resampling/Resampling.html for some further information

What is a p value? It is the probability that an event will occur.

What does a p value mean in the context of hypothesis testing? The probability of observing results as or more extreme than those obtained if the null hypothesis were true.

Are reported p-values always accurate? No. Often p-values are calculated based on assumptions about the distribution of error. If these assumptions, such as normality and homogeneity of variance, are violated, there is no guaranty that the p-value will be accurate. The degree to which the p-values are inaccurate tends to depend on the severity of the violation.

Bootstrapping is a way of overcoming issues associated with inaccurate p-values that result from violations of parametric assumptions. Bootstrapping also allows for the production of tests of statistical significance that do not have easily representable sampling distributions, such as the median.

Some authors suggest (see Howell for a discussion) that bootstrapping approaches will takeover the standard approaches to testing statistical significance.

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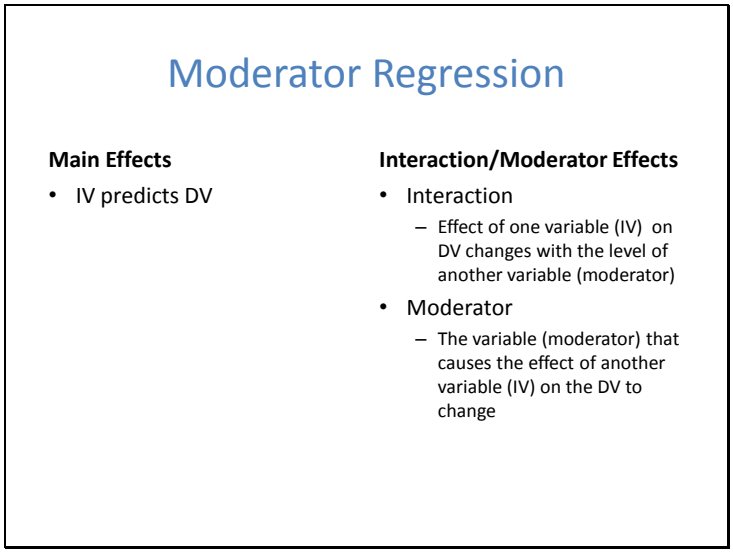

Main effect:
A main effect of X on Y is what we normally mean by a relationship between two variables.
Examples:
Correlation: conscientiousness is correlated with performance
Main effect in ANOVA: Faculty of the university you are predicts satisfaction ratings
Normal regression coefficient: ability predicts performance in a regression model with other predictors such as past experience and

Interaction Effect:
This is when the effect of one variable is altered by another variable.
Graphically it means that the regression line between the IV and the DV is different across the levels of another variable.
Interaction and moderation are referring to the same ideas. Moderator regression puts the focus on the moderating effect (i.e., the interaction). It also involves deciding usually based on theoretical grounds which of the two predictor variables is the moderator. For example if we suggested that locus of control moderates the job satisfaction-performance relationship, we could say equally that job satisfaction moderates the locus of control-performance relationship, but that might not be as aligned with our theoretical orientation.

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Why many people's tests of **moderation** are misguided

- Incorrect Interpretation
  - Two main effects is not an interaction effect
  - Some apparent interactions are an artefact of multicollinearity with main effects and result from incorrectly running the model
- Often Unimportant
  - Main effects tend to be the main story, most of the time

Two main effects is not an interaction:

In many cases, people confuse two main effects with an interaction. If we have a model of performance which suggests intelligence and motivation are predictors of task performance. In everyday language people may say that motivation compensates for lower ability. Such everyday language may or may not imply an interaction effect. When doing the research the more common situation is that motivation is important and intelligence is important. Thus, the best performers are those who are both intelligent and motivated and the worst performers tend to be those who are low on intelligence and with low motivation. This seems to be particularly the case in field studies where we observe the normal variation of our variables.

Main effects tend to be the main story, most of the time:

There is often a push to do "fancy analyses" in a thesis or journal article in order to appear as if we are being innovative. Moderator regression, mediation analysis, and structural equation modelling are all examples of these. While these methods all have their merits, the key thing is to align the technique with the research question and listen to what the data is telling us. Most of the time, the large effects observed in field study are at the level of main effects. Where interactions are observed, they tend to be fairly small. Thus, when thinking about the correlates and causes of a particular outcome, it is important to pay attention to effect sizes of the main effects and the interaction effects. Most of this time, this will yield an understanding that suggests, more of X means more of Y and the relationship between X and Y is not altered substantially by how much of the moderator you have.

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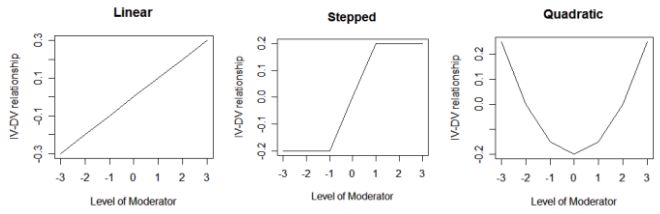
Types of Interaction

- Independent Variable
  - Metric; Binary; Nominal
- Moderator Variable
  - Metric; Binary; Nominal
- Nature of moderator effect



Nature of moderator effect: Moderator variables alter the relationship between the independent variable and the dependent variable. At particular levels of the moderator the IV-DV relationship will be stronger or weaker. In some situations the direction of the relationship between the IV and the DV will change from positive to negative. If you conceptualise the effect of a metric moderator variable it is important to think about how the IV-DV relationship is moderated by the moderator. At what levels of the moderator will the relationship between IV and DV be strongest or weakest. The above graphs are similar to those discussed in Barron & Kenny (1986). While there are several choices for how you might show the scale of the moderator and the scale of the IV-DV relationship, the above graphs imply a z-score for the moderator and a correlation for the IV-DV relationship.

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Moderator Regression
Overview of Procedural Steps

- 1. Create Interaction Variable
  - Centre the two main effects: score – mean
  - Multiply the two centred main effects
- 2. Enter two main effects into hierarchical regression in step 1
- 3. Enter the interaction term in step 2
- 4. Examine r-square change statistic
- 5. If statistically significant and practically important, Follow-up with analysis of simple slopes

It's important to know the process, but there are SPSS macros to facilitate the process.

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Create interaction variable

1. Restructure independent and moderator variable
   - Centre Metric Variables
     - Subtract the mean from the variable
   - Recode nominal variables
     - Dummy; effects; other contrasts
2. Multiply restructured independent and moderator variable

The **basic idea** of an interaction variable involves multiplying the independent variable and the moderator variable to create an interaction term.

Centre metric variable: It is often suggested that we should centre our variables prior to creating this interaction term. Centring involves subtracting the mean from the independent variable and the moderator variable. This reduces the correlation between the interaction term on the one hand the moderator and independent variable on the other hand. This makes it easier to attribute variance to the interaction term as opposed to the main effects. It also may make interpretation of the regression coefficients clearer.

It should be noted that centring does not alter the statistical significance or size of the r-square change statistic, when testing the interaction term in a subsequent step to the main effects. Thus, whether you centre or not, you get the same answer to your research question regarding moderation.

Recode nominal variables: Nominal variables (i.e., those with 3 or more values) need to be recoded to be included in a test of moderation. The number of groups minus one binary variables need to be created. This commonly involves using dummy coding, whereby one level of the variable is made a reference category and then a series of dummy variables are created to represent belonging to every other category. Other categorisation schemes are possible.

Multiply restructured variables: To form the interaction term that will be used to test the moderation hypothesis, the independent and the moderator variable need to be multiplied together to create a third variable (the interaction). In the case of two metric variables, this simply involves multiplying the two centred versions of the variables. When one of the variables is nominal, the centred metric variable needs to be multiplied by all the binary variables that were created by the recode (e.g., dummy coding). This yields multiple interaction variables representing what is conceptually a single moderator effect. This set of interaction variables are then entered together as a group as a test of the moderator hypothesis.

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Run hierarchical regression

- Step 1 – Main Effects
- Step 2 – Interaction Term
- R-square
- R-square change
- ANOVA for R-square

A hierarchical regression is a form of regression whereby predictor variables are entered in a series of steps. Each subsequent step includes all the predictors of the previous steps as well as one or more additional predictors. Hierarchical regression is the standard way to test for moderator effects.

Step 1: The main effect variables are entered into the regression. This includes the independent variable and the moderator variable. Optionally, there could be a range of other predictors in this first step. When developing a model for predicting a particular outcome, researchers often want to combine a set of variables as well as one or two moderator effects. If you wish to test the moderator effect in the context of other predictors, it is usually beneficial to also test it with just the independent variable and the moderator variable to see whether any interaction does or does not show up in the simple version of the model.

Step 2: The interaction term is added in the second step. As mentioned earlier, if either the main effect or moderator is nominal, this will mean that there are multiple interaction terms to be included in this step.

R-square: R-square represents the percentage of variance explained in the dependent variable by the best weighted linear composite of the predictor variables. It ranges from zero to one, where one represents 100% of the variance explained.

R-square change: R-square change is the increase in r-square that results from the inclusion of one or more variables into a regression model. In the context of testing for moderator effects, if the size of the r-square change for step 2 when the moderator term was introduced is an indicator of the size of the moderator effect.

ANOVA for R-square: Both r-square and r-square change have associated ANOVAs which test whether they are statistically significant. They test the null hypothesis that the population r-square or r-square change is zero. In general, bigger sample sizes and bigger r-squares (or r-square changes) yield smaller p-values.

If the r-square change is statistically significant (e.g., p is less than alpha – typically .05) after the inclusion of the moderator term, this indicates that there is a statistically significant moderator effect.

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Follow up: Understanding coefficient

- Core Question?
  - How does the moderator moderate the relationship between IV and DV?
- Some ways of answering the question
  - Scatterplots
    - IV by DV with different points for different levels of the moderator
  - Analysis of simple slopes
    - Provide an estimate of the regression slope between IV and DV for different levels of moderators
    - Plot these regression slopes

Simple Slopes web application: http://www.psych.ku.edu/preacher/interact/mlr2.htm
SPSS macro for calculation: http://web.uni-frankfurt.de/fb05/psychologie/Abteil/sozial/materialien/TWOWAY%20macro.pdf

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Is there a stronger relationship between abilities and task performance for participants who felt the ability tests were an accurate reflection of their abilities?

- Note:
  - For this analysis I used an overall ability score and a yes/no question (do you think the ability tests were an accurate reflection of your abilities?)
- Inspiration of Question:
  - It is probable that tests may reflect the potential to perform well on a task for some people better than others
  - Do people have insight into this potential for tests to predict?
- Which statistical test do we use
  - Binary and continuous predictor
  - Continuous dependent variable
  - Concerned with interaction of two predictors
  - Answer: Moderator Regression

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Descriptive Statistics

Descriptive Statistics

	Mean	Std. Deviation	N
TEP: Average Text Editing Performance (Seconds)	38.0070	12.87296	94
Q7) Do you feel the tasks were an adequate means to assessing your ability?	.78	.419	94
Z Score: Total Ability	.154	.9224	94
Ability by QA7 Interaction	1226	70210	94

Correlations

Pearson Correlation

	TEP: Average Text Editing Performance (Seconds)	Q7) Do you feel the tasks were an adequate means to assessing your ability?	Z Score: Total Ability	Ability by QA7 Interaction
TEP: Average Text Editing Performance (Seconds)	1.000	-.046	-.627	-.503
Q7) Do you feel the tasks were an adequate means to assessing your ability?	-.046	1.000	.036	.091
Z Score: Total Ability	-.627	.036	1.000	.856
Ability by QA7 Interaction	-.503	.091	.856	1.000

- Think about the metrics of the variables
  - Text editing: Seconds
  - Q7: 0=No; 1 = Yes
  - Ability: Z-score (although some missing cases result in mean not exactly equalling zero)
  - Interaction term: result of multiplying Q7 by ability

SPSS SYNTAX for creating interaction
compute qa7BYzztotal = qa7 * zztotal.

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3.2 Model

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.622[a]	.386	.373	10.18378	.386	28.343	2	90	.000
2	.626[b]	.392	.371	10.19775	.005	.754	1	89	.388

a. Predictors: (Constant), Zztotal Z Score: Total Ability, qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?

b. Predictors: (Constant), Zztotal Z Score: Total Ability, qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?, qa7BYzztotal Ability by QA7 Interaction

c. Dependent Variable: tep_overall TEP: Average Text Editing Performance (Seconds)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5878.972	2	2939.486	28.343	.000[a]
	Residual	9333.846	90	103.709		
	Total	15212.818	92			
2	Regression	5957.348	3	1985.783	19.095	.000[b]
	Residual	9255.470	89	103.994		
	Total	15212.818	92			

a. Predictors: (Constant), Zztotal Z Score: Total Ability, qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?

b. Predictors: (Constant), Zztotal Z Score: Total Ability, qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?, qa7BYzztotal Ability by QA7 Interaction

c. Dependent Variable: tep_overall TEP: Average Text Editing Performance (Seconds)

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Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	39.917	2.225		17.941	.000	35.497	44.338
	qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?	-.709	2.527	-.023	-.281	.780	-5.728	4.311
	Ztotal Z Score: Total Ability	-8.721	1.161	-.621	-7.513	.000	-11.027	-6.415
2	(Constant)	40.070	2.235		17.930	.000	35.629	44.510
	qa7 Q7) Do you feel the tasks were an adequate means to assessing your ability?	-.955	2.546	-.031	-.375	.708	-6.014	4.103
	Ztotal Z Score: Total Ability	-10.368	2.225	-.738	-4.660	.000	-14.790	-5.947
	qa7BYztotal Ability by QA7 Interaction	2.265	2.609	.138	.868	.388	-2.920	7.450

a. Dependent Variable: tep_overall TEP: Average Text Editing Performance (Seconds)

- Construct separate regression equation for those who said yes and no to Q7?
- Yes: 40.07 - 0.98 -10.37Ability + 2.21Ability = 39.09 – 8.16Ability
- No: 40.07 -10.37Ability
- Looking at the two regression equations, we see that they look very similar.
- If anything there is a stronger relationship between ability and task performance for participants who felt that the ability tests were not an accurate reflection of their ability

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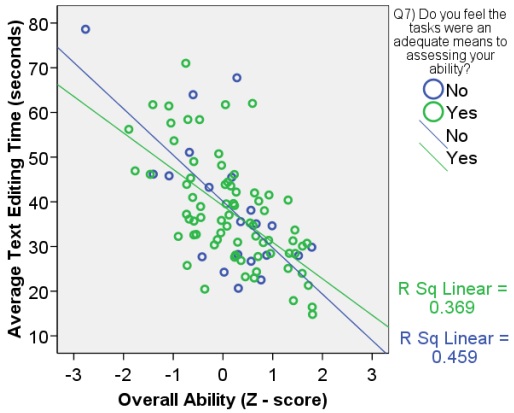
Exploring scatterplot for two groups



This graph was obtained using SPSS scatterplot graph feature and the “Set Markers by” group option. Once the graph was obtained, double clicking on the graph allows one to request group regression lines. If the moderator was continuous, I would recode it into a set of 2 to 5 ordered categories purely for the purpose of generating this greaph to explore the changing nature of the relationship between IV and DV across different levels of the moderator.

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3.2 Casewise diagnostics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	21.5581	68.7269	38.0070	8.13274	94
Std. Predicted Value	-2.023	3.777	.000	1.000	94
Standard Error of Predicted Value	1.187	6.699	1.918	.841	94
Adjusted Predicted Value	19.6907	61.0852	37.9268	7.94603	94
Residual	-21.62953	30.58702	.00000	9.97857	94
Std. Residual	-2.132	3.015	.000	.984	94
Stud. Residual	-2.153	3.093	.003	1.006	94
Deleted Residual	-22.04189	32.17301	.08013	10.45744	94
Stud. Deleted Residual	-2.198	3.253	.007	1.021	94
Mahal. Distance	.285	39.567	2.968	4.782	94
Cook's Distance	.000	.325	.013	.037	94
Centered Leverage Value	.003	.425	.032	.051	94

Issue	Rule of thumb	Status
Distance	Studentised residuals > ±3.0	At least one case (e.g., 3.25)
Leverage	2*p/N = 2*3/94 = .064 High leverage means > .064	At least one case with 'large' leverage values (e.g., .43)
Influence	Cook's D > 1	No cases

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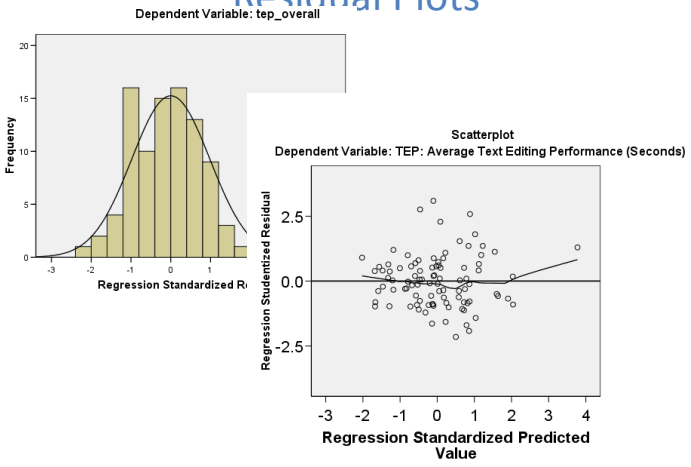
Residual Plots



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Mediation & Moderation Concluding Comments

- Mediation:
  - Explain the process by which two variables relate
- Moderation:
  - Explain contextual or other factors that alter relationship between two variables
- Tools for achieving conceptual clarity

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General Review

- Thinking about the last 5 sessions
  - What were the core themes?
  - What is the next step?
  - How does it relate to your thesis?
  - How does it relate to your professional development?
  - What is your self-development strategy for implementing the right techniques in your thesis and beyond?