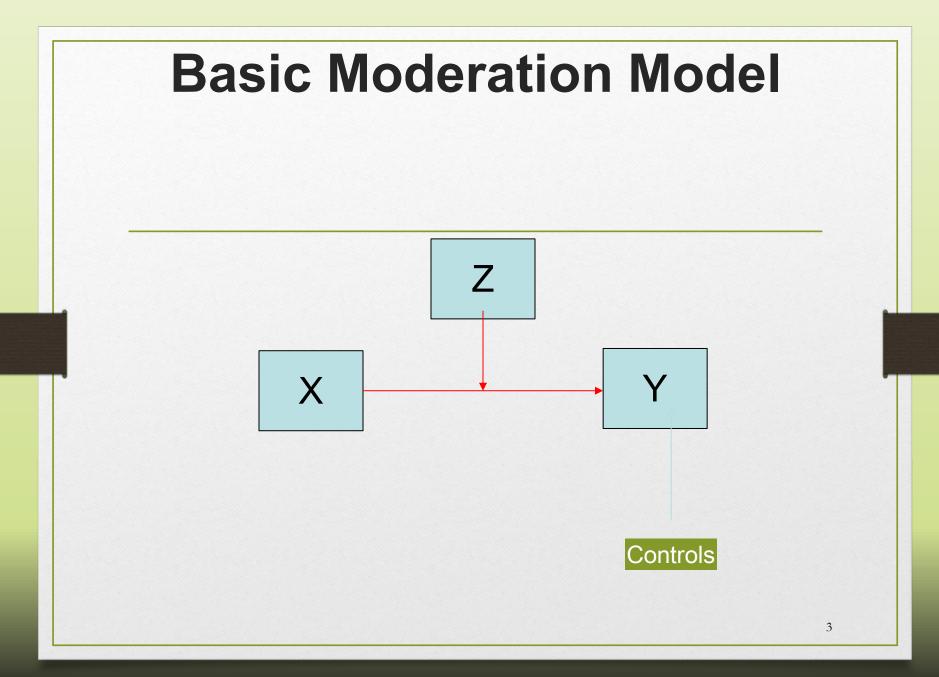
## Moderated Mediation or Mediated Moderation

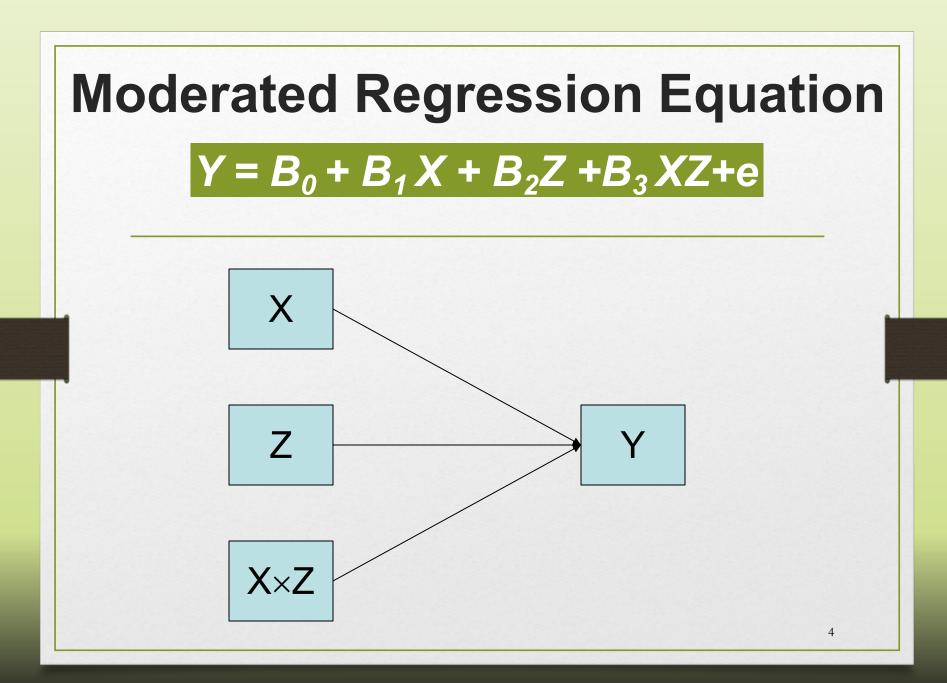
**Robert Pavur University of North Texas** 

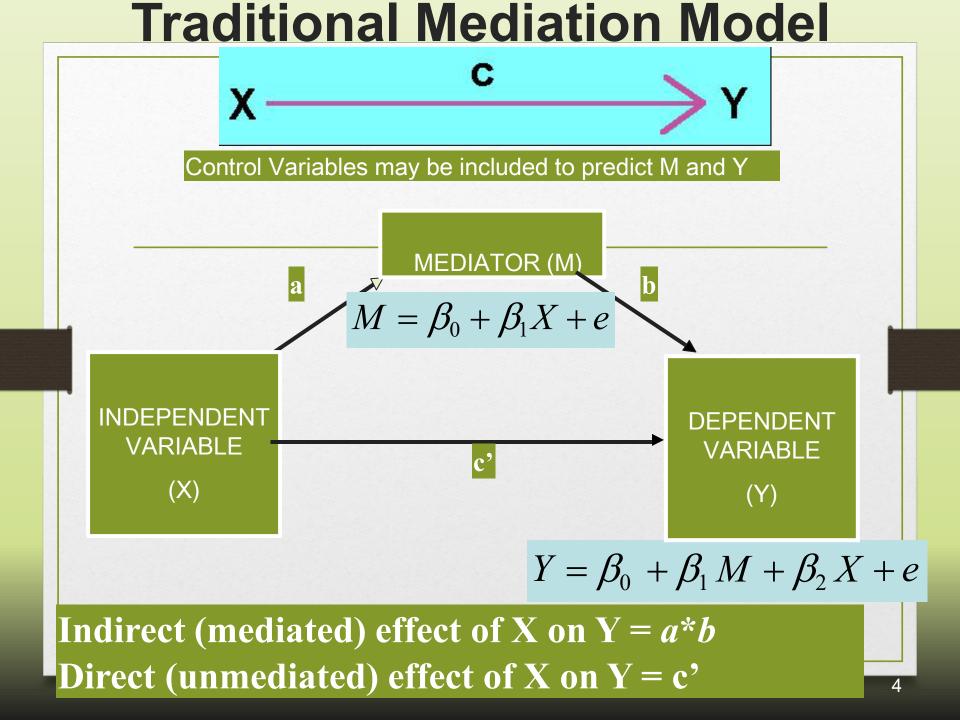
### **Mediation and Moderation**

- A *moderator* variable influences the strength of a relationship between two other variables and is associated with interactions of variables.
- A model of the relationship of X and Y is said to be "conditional" on the value of W if W moderates that relationship
  - A *mediator* variable explains the relationship between the two other variables and is associated with a path diagram.
  - <u>Mediation is part of a causal chain of events or process</u>. When the effect of a mediator is in a path model, the strength of the relationship between the independent and dependent variables may decrease.

 Theory and literature support determining variables that are mediators or moderators.
 Note: Causal support with cross-sectional data requires additional justification.

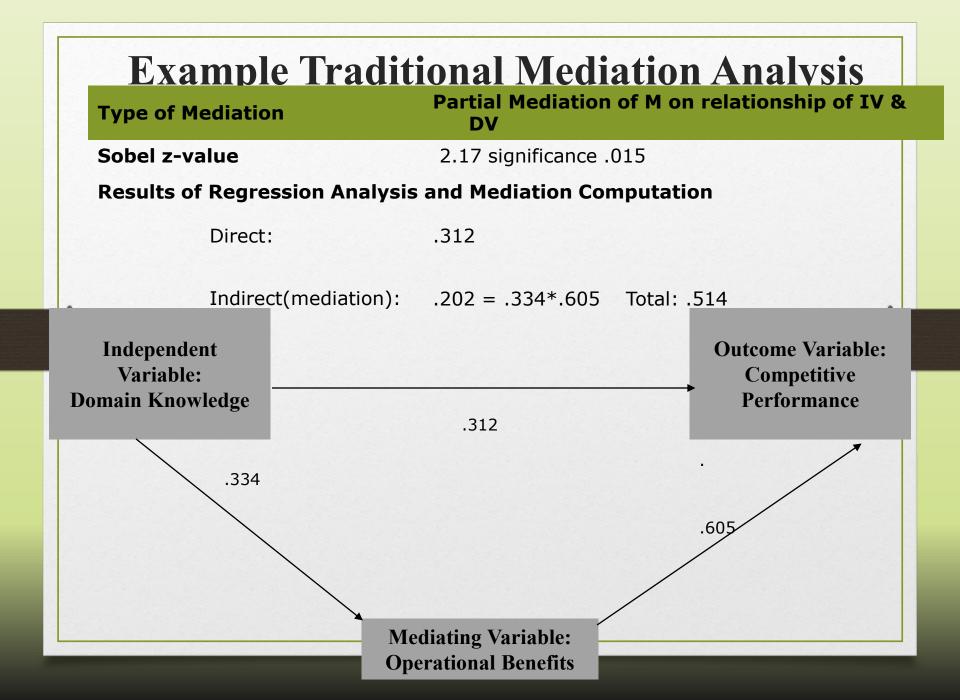






# Why Use Bootstrap to test for Significance of Indirect Effect?

- Test for mediation or indirect effect is  $H_0: ab = 0$ .
- Sobel Z test is called the "normal theory" test and assumes the indirect effect is normally distributed. Several alternative tests exists (Hayes & Scharkow, 2013 for a review).
- The distribution of the indirect effect tends to be skewed, and thus the normal distribution assumption is questionable.
- Bootstrapping is a nonparametric approach that can provide bootstrapped confidence intervals for the indirect effect and usually has more power than the "normal theory" tests when data are highly skewed.



#### Baron & Kenny (1986) MacKinnon, Hayes, Preacher (2010)



## Traditional and Modern Mediation Pioneers



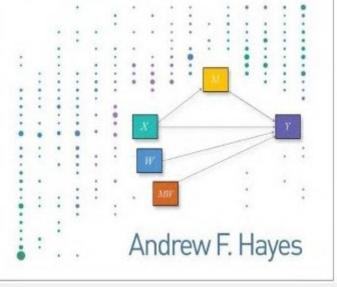
#### **Hayes Provides Process Macros**

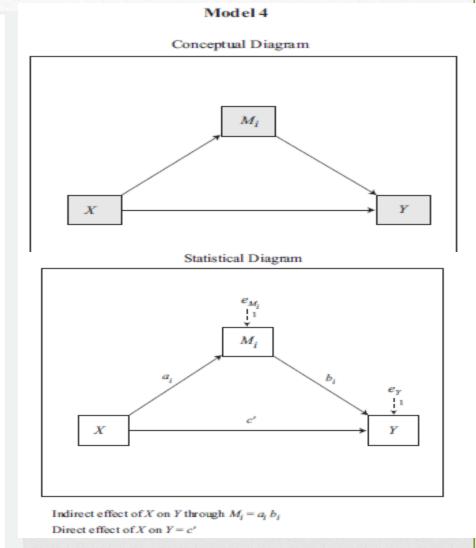
- Many software packages compute the indirect effects. If it is significant, then mediation is supported. (Whether it is consistent mediation may be another problem.)
- Hayes created Process Macros in 2012 to use
  bootstrapping to test significance of the indirect
  effect in path models using regression analysis.
- His contribution is that he has a template of models that can be selected and indirect effects and their contrasts can be analyzed.
- Template allows multiple mediators and moderators.

#### Hayes Process Textbook & Templates

#### SECOND EDITION

Introduction to Mediation, Moderation, and Conditional Process Analysis | A Regression-Based Approach







#### Mediation, Moderation and Conditional Process Analysis

Online and in-person courses by Andrew F. Hayes in July 2023

Enroll at ccramsessions.com

Take a class from me on the topic of this book.

#### Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach Third Edition

#### THIRD EDITION

Introduction to Mediation, Moderation, and Conditional Process Analysis



Introduction to Mediation, Moderation, and Conditional Process Analysis describes the foundation of mediation and moderation analysis as well as their analytical integration in the form of "conditional process analysis", with a focus on PROCESS for SPSS SAS, and R (#processmacro) as the tool for implementing the methods discussed. Available as both an e-book and in print form, it is published by The Guilford Press.

Here are the data files and code used in this third edition of the book. Here is the errata for the third edition.

## Andrew F. Hayes, Ph.D.

Home

My C.V.

My Books

Teaching and Speaking

Mechanisms and **Contingencies Lab** 

**PROCESS** macro for SPSS, SAS, and R

SPSS, SAS, and R Macros and Code

Video

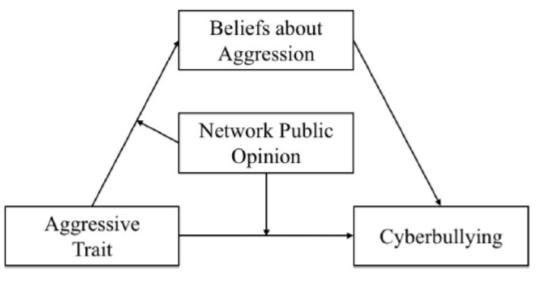
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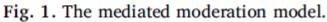


random sample of size n from samp

Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach Second Edition

**Effects** of Aggressive **Traits on Cyberbullying**: Mediated moderation or moderated mediation? By Song, Zhu, Liu, Fan, Zhu, and Zhang (2019) **Computers** in Human **Behavior** 





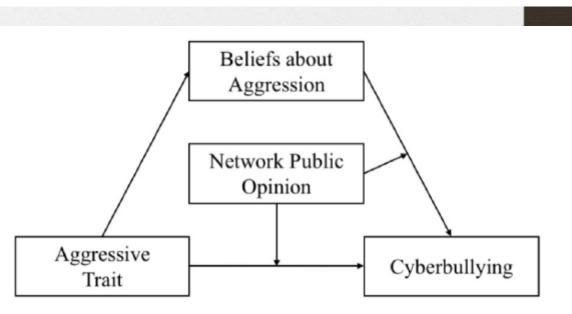
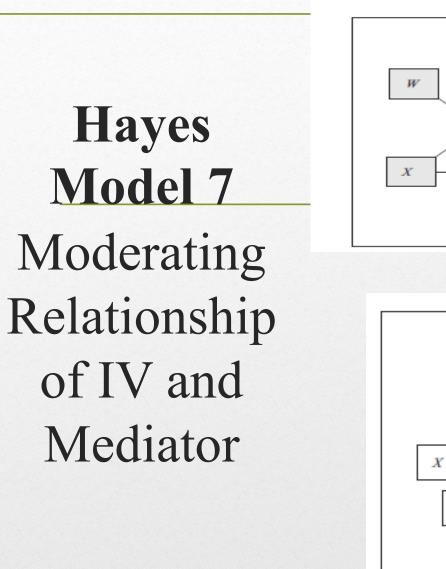
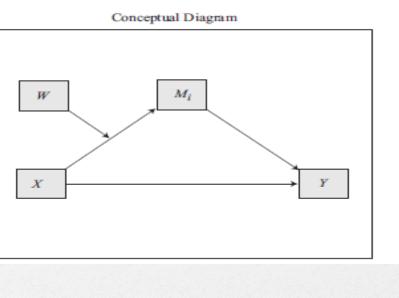
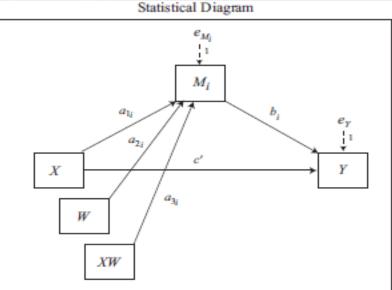


Fig. 2. The moderated mediation model.

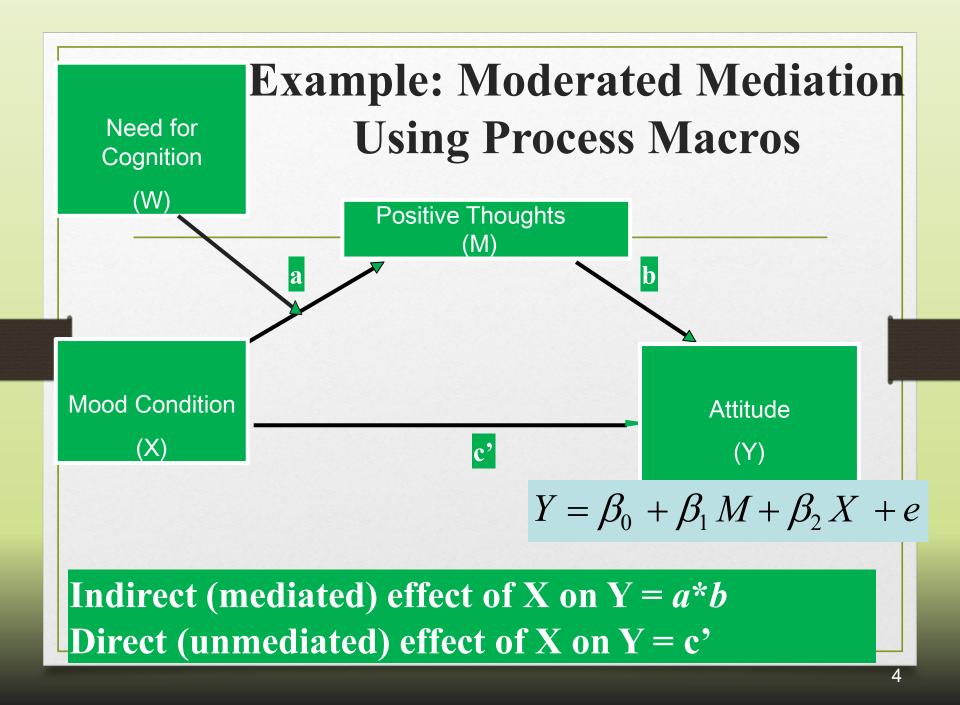
Model 7







Conditional indirect effect of X on Y through  $M_i = (a_{1i} + a_{3i}W)b_i$ Direct effect of X on Y = c'



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1	4		4	-1	43824	.43824	2.87	-1.2563	-7.2256	
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(	6		6	-1	.43842	43842	-13.14	-5.7593	-24.1241	
	7		7	-1	-1.09646	1.09646	95	1.0451	-28.0378	
(	8		8	-1	57737	.57737	-13.77	7.9523	-9.4845	
	9		9	-1	1.75978	-1.75978	-5.82	-10.2359	10.8746	

#### Hayes SPSS Add-ins

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## **Specify Model 7 for this Analysis**

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#### PROCESS\_v3.5

Variables:			Y variable:	About
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Mood x NFC [MOODNFC]			X variable:	-
Positive thoughts x NFC [POSNFC]		•	🚓 MOOD	Multicategorical
			Mediator(s) M:	Long variable names
			Positive thoughts [POS]	
		\$		
			Covariate(s):	
Model number:		\$		
7	~			
Confidence intervals				
95	~		Moderator variable W:	
Number of bootstrap samples		-	Need for cognition [NFC]	
5000	~		Moderator variable Z:	
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## **Process Options**

#### PROCESS options

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Doc	Written by Andrew F. Hayes, Ph.D. www.afhayes.com cumentation available in Hayes (2018). www.guilford.com/p/hayes3	
Model Y	: 7 : ATT : MOOD	
	: POS : NFC	
-	100	
Sample Size:	100	

#### Standard Regression Analysis

POS

Model Summar	У					
R	R-sq	MSE	F	df1	df2	p
.5656	.3200	48.5739	15.0557	3.0000	96.0000	.0000
Model						
	coeff	se	t	р	LLCI	ULCI
constant	.0404	.6971	.0579	.9540	-1.3435	1.4242
MOOD	4.3357	.6971	6.2193	.0000	2.9519	5.7196
NFC	.7672	.5130	1.4956	.1380	2510	1.7854
Int_1	1.2565	.5130	2.4496	.0161	.2383	2.2747
Product term	s key:					
Int_l :	MOOD	х	NFC			
Test(s) of h	-					
R2-ch	ng	F d	lfl d	lf2	р	
X*W .04	25 6.000	5 1.00	96.00	.00	161	

# **Conditional Effects of X(Mood) at values of W(Need for Cognition)**

Focal predict: MOOD (X)

Mod var: NFC (W)

Conditional effects of the focal predictor at values of the moderator(s):

NFC	Effect	se	t	р	LLCI	ULCI
-1.0841	2.9735	.8894	3.3434	.0012	1.2081	4.7389
.0018	4.3380	.6972	6.2225	.0000	2.9542	5.7219
1.4457	6.1523	1.0206	6.0281	.0000	4.1264	8.1782

	Predictors of Attitude							
OUTCOME VARI	ABLE:							
ATT								
Model Summar	:У							
R	R-sq	MSE	F	dfl	df2	p		
.6356	.4039	171.5940	32.8662	2.0000	97.0000	.0000		
Model								
	coeff	se	t	р	LLCI	ULCI		
constant	1.9807	1.3099	1.5121	.1338	6192	4.5806		
MOOD	1.7844	1.5343	1.1631	.2477	-1.2607	4.8295		
POS	1.1571	.1853	6.2450	.0000	.7894	1.5248		

S	U			ect Ef irect F	fect and
	Cond			ITECT F	liects
*****	***** DIREC	I AND INDII	RECT EFFECT:	5 OF X ON Y	******
Direct effect	t of X on Y				
Effect	se	t	р	LLCI	ULCI
1.7844	1.5343	1.1631	.2477	-1.2607	4.8295
Conditional :	indirect effe	ects of X (	on Y:		
INDIRECT EFF	ECT:				
MOOD	-> POS	->	ATT		
NFC	Effect	BootSE	BootLLCI	BootULCI	
-1.0841	3.4406	1.2170	1.3189	6.0246	
.0018	5.0195	1.1817	2.9481	7.5305	
1.4457	7.1187	1.6595	4.1985	10.6781	

### Conditional Indirect Effects, Contrasts, and Index of Moderated Mediation

Conditional indirect effects of X on Y:

INDIRECT EFFECT:										
D -	-> POS	->	ATT							
NFC	Effect	BootSE	BootLLCI	BootULCI						
-1.0841	3.4406	1.2170	1.3189	6.0246						
.0018	5.0195	1.1817	2.9481	7.5305						
1.4457	7.1187	1.6595	4.1985	10.6781						
Index of moderated mediation:										
Index	K BootSH	E BootLLC	I BootUL	CI						
1.4539	9.6344	4 .347:	1 2.84	62						
Pairwise contrasts between conditional indirect effects (Effectl minus Effect2)										
Effectl	Effect2	Contrast	BootSE	BootLLCI	BootULCI					
5.0195	3.4406	1.5789	.6889	.3769	3.0908					
7.1187	3.4406	3.6781	1.6048	.8781	7.2003					
7.1187	5.0195	2.0992	.9159	.5012	4.1095					
	NFC -1.0841 .0018 1.4457 Index of Index of 1.4539 rwise cont Effect1 5.0195 7.1187	DD -> POS NFC Effect -1.0841 3.4406 .0018 5.0195 1.4457 7.1187 Index of moderated Index BootSP 1.4539 .6344 rwise contrasts betwee Effect1 Effect2 5.0195 3.4406 7.1187 3.4406	DD         ->         POS         ->           NFC         Effect         BootSE         -           -1.0841         3.4406         1.2170         .0018         5.0195         1.1817           .0018         5.0195         1.1817         1.6595         .           Index of moderated mediation:         Index         BootSE         BootLLC:           1.4539         .6344         .3473           .rwise contrasts between condition         Effect1         Effect2         Contrast           5.0195         3.4406         1.5789         7.1187         3.6781	NFC         Effect         BootSE         BootLLCI           -1.0841         3.4406         1.2170         1.3189           .0018         5.0195         1.1817         2.9481           1.4457         7.1187         1.6595         4.1985           Index of moderated mediation:         Index         BootSE         BootLLCI         BootUL           1.4539         .6344         .3471         2.84           rwise contrasts between conditional indir           Effect1         Effect2         Contrast         BootSE           5.0195         3.4406         1.5789         .6889           7.1187         3.4406         3.6781         1.6048	DD -> POS -> ATT NFC Effect BootSE BootLLCI BootULCI -1.0841 3.4406 1.2170 1.3189 6.0246 .0018 5.0195 1.1817 2.9481 7.5305 1.4457 7.1187 1.6595 4.1985 10.6781 Index of moderated mediation: Index BootSE BootLLCI BootULCI 1.4539 .6344 .3471 2.8462 rwise contrasts between conditional indirect effects Effect1 Effect2 Contrast BootSE BootLLCI 5.0195 3.4406 1.5789 .6889 .3769 7.1187 3.4406 3.6781 1.6048 .8781	ND         ->         POS         ->         ATT           NFC         Effect         BootSE         BootLLCI         BootULCI           -1.0841         3.4406         1.2170         1.3189         6.0246           .0018         5.0195         1.1817         2.9481         7.5305           1.4457         7.1187         1.6595         4.1985         10.6781           Index of moderated mediation:         Index         BootSE         BootLLCI         BootULCI           1.4539         .6344         .3471         2.8462           rwise contrasts between conditional indirect effects (Effect1 minus           Effect1         Effect2         Contrast         BootSE         BootLLCI           5.0195         3.4406         1.5789         .6889         .3769         3.0908           7.1187         3.4406         3.6781         1.6048         .8781         7.2003				

Moderator value(s) defining Johnson-Neyman significance region(s):

Value % below % above -1.6949 10.0000 90.0000

Conditional effect of focal predictor at values of the moderator:

		-				
NFC	Effect	se	t	р	LLCI	ULCI
-4.8265	-1.7288	2.5683	6731	.5025	-6.8270	3.3693
-4.4314	-1.2324	2.3739	5191	.6049	-5.9446	3.4798
-4.0363	7359	2.1810	3374	.7365	-5.0651	3.5933
-3.6411	2394	1.9900	1203	.9045	-4.1896	3.7107
-3.2460	.2570	1.8016	.1427	.8868	-3.3191	3.8331
-2.8509	.7535	1.6166	.4661	.6422	-2.4554	3.9624
-2.4558	1.2500	1.4364	.8702	.3864	-1.6012	4.1012
-2.0607	1.7464	1.2630	1.3828	.1699	7606	4.2535
-1.6949	2.2061	1.1114	1.9850	.0500	.0000	4.4122
-1.6656	2.2429	1.0997	2.0395	.0441	.0600	4.4258
-1.2705	2.7394	.9517	2.8785	.0049	.8503	4.6285
8753	3.2358	.8271	3.9121	.0002	1.5940	4.8777
4802	3.7323	.7381	5.0566	.0000	2.2672	5.1974
0851	4.2288	.6983	6.0561	.0000	2.8427	5.6148
.3100	4.7253	.7159	6.6004	.0000	3.3042	6.1463
.7051	5.2217	.7872	6.6337	.0000	3.6592	6.7842
1.1002	5.7182	.8994	6.3581	.0000	3.9330	7.5034
1.4953	6.2147	1.0393	5.9794	.0000	4.1516	8.2778
1.8904	6.7111	1.1974	5.6047	.0000	4.3343	9.0880
2.2856	7.2076	1.3673	5.2714	.0000	4.4935	9.9217
2.6807	7.7041	1.5451	4.9861	.0000	4.6370	10.7711
3.0758	8.2005	1.7284	4.7446	.0000	4.7697	11.6314

Johnson-Neyman Option

## Links & References

http://www.afhayes.com/introduction-to-mediation-moderation-andconditional-process-analysis.html

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# **Thanks for your attendance!** Questions? Comments?