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SBM POSTGRADUATES TALK SERIES 2

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HOUSTON WE HAVE 13 PROBLEMS

THE MYTH AND TRUTH ABOUT MEDIATION & MODERATION

MODERATION & MEDIATION

- Yet another methodological topic? Is this really necessary?
- Yes, not just a "mere methodological" issue or "quibbles of stats
- geeks"
- Central to theory building and testing
- Central to understanding management and organizations
- Critical for understanding when and why organizational practices are effective
- Directly related to **how we do research** with implications for replicability, trustworthiness, and credibility of our results and conclusions

MODERATION

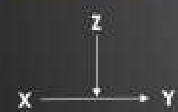
- *The conditions under which and effect varies in size*

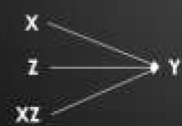
MEDIATION

- *The underlying mechanism and processes that connect antecedents and outcomes*

MODERATOR

Moderation





Continuous Moderator

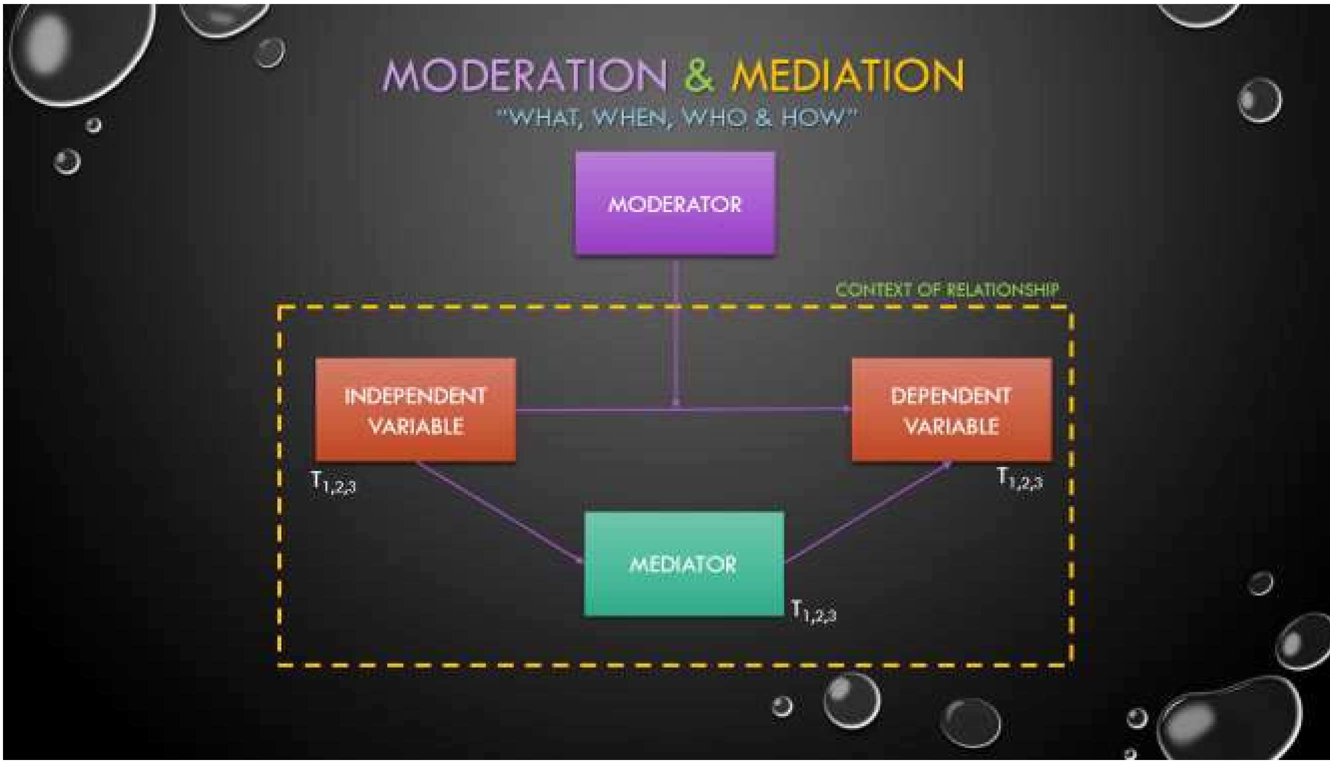
A moderator variable influences the nature (magnitude/direction) of the effect of an antecedents on an outcome.

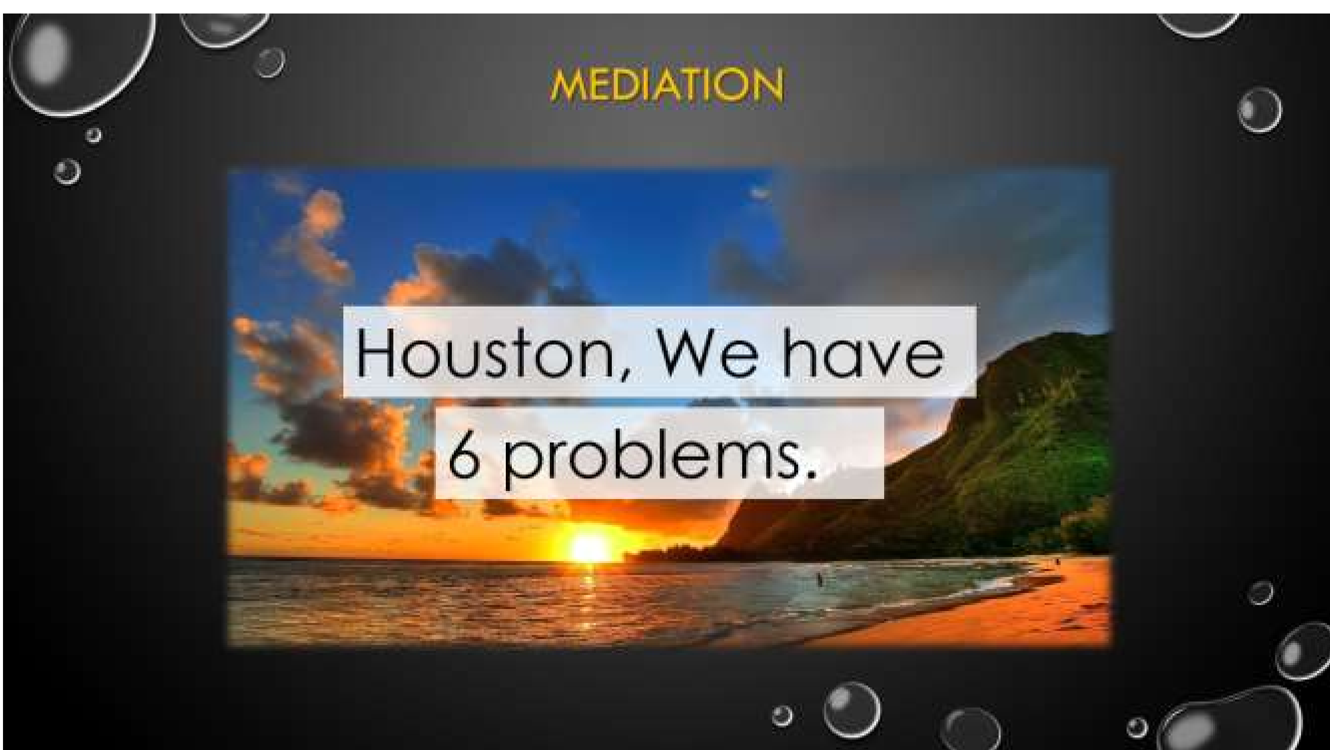
- Two types of moderator variable:
  - *Categorical Moderator*
  - *Continuous Moderator*
- When moderator is ***categorical***, the traditional data-analytic approach is subgrouping analysis that is by comparing correlation or regression coefficients across various categories.
- When moderator is ***continuous***, the study relies on **moderated multiple regression.** This regression consists of a predictor, X, a second predictor Z, which is the moderator, and a product term between X and Z, which carries information on the moderating effect of Z on the X-Y relation.

MEDIATOR

A **mediator** transmits the effect of antecedents on the outcome, either in part or whole (Baron & Kenny, 1086; MacKinnon, 2008)

- **Direct effect** of X on Y indicates that there is no mediation (path c)
- **Indirect effect** of X on Y indicates that the effect of X on Y can be transmitted only through variable M with the magnitude of this effect represented by the products of path a and b (a*b)
- **Direct + Indirect effect** of X on Y indicates that the effect of X on Y can be transmitted directly from X on Y (path c') or indirectly through a mediator, M (path a*b)


MODERATION & MEDIATION
"WHAT, WHEN, WHO & HOW"
MODERATOR
CONTEXT OF RELATIONSHIP
INDEPENDENT VARIABLE
DEPENDENT VARIABLE
$T_{1,2,3}$
$T_{1,2,3}$
MEDIATOR
$T_{1,2,3}$


MEDIATION
Houston, We have
6 problems.

MEDIATION PROBLEM 1

Requiring a Significant Total Effect Between the Antecedent and the Outcome:

- X-Y relation as a first step in the mediation test.
- If the direct effect c' is significant and positive
- And the indirect effect ab is significant and negative....
- The total X-Y effect could be zero: c = c' + (-ab) ≈ 0

MEDIATION SOLUTION 1

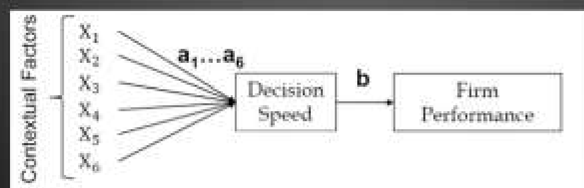
$$Y = cX + e_y$$
$$M = aX + e_2$$
$$Y = bM + c'X + e'_Y$$

- We should focus on the paths that constitute the mediation effect.
- These are necessary and sufficient to establish mediation

MEDIATION PROBLEM 2

Disregarding the Magnitude of Indirect Effect

- Evaluating the size of the mediating effect is critical for understanding alternative mediating mechanisms



- Although they may all be statistically significant, we do not know their relative importance without comparing the mediating effects

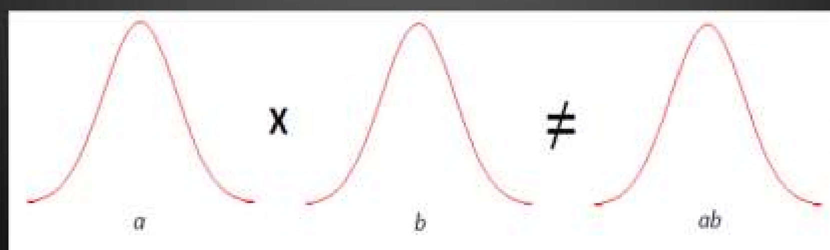
MEDIATION SOLUTION 2

- The Sobel test is a common method of testing the mediated effect that is **not appropriate** to use
  - Product of the coefficients divided by the estimate of its standard error
  - Assumes the product of the coefficients is normally distributed

- Nonparametric testing procedures are available that do not rely on assumptions of normality
  - Percentile-based confidence intervals derived using the bootstrap (e.g., Gottfredson & Aguinis, in press, JOB)
  - Variance Accounted For (VAF) (Zhao et al., 2010)
  - Method of choice for future research using mediation (i.e., Monte Carlo method for mediation)

MEDIATION SOLUTION 2

For the Sobel test, the p-value is derived by assuming normality of the sampling distribution of the indirect effect and using the standard normal distribution. In condition where *path a* (X-> M) and *path b* (M->Y) are normally distributed, the product of *path a* and *path b*, namely *path a*b* is not normally distributed. Hence, using Sobel test to access size of mediation violates Sobel test's underlying assumption on normal sampling distribution.



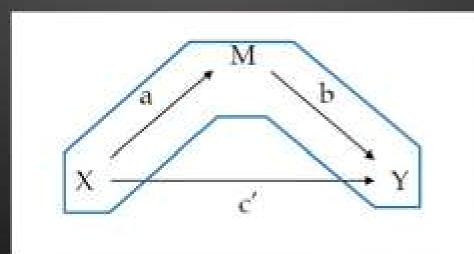
MEDIATION PROBLEM 3

Testing the Direct Effect as a Condition for Mediation

- Testing c' was included in the original causal-steps procedure .
- This need not be considered when determine whether brand attitude mediated the effect of adverts on brand choice.
- This step can cause researchers to overlook meaningful mediating processes.

MEDIATION SOLUTION 3

- Future research should conclude that mediation exists when the indirect effect is supported.
- Past research has dismissed significant indirect effect when the direct effect remained significant in the final steps



MEDIATION PROBLEM 4

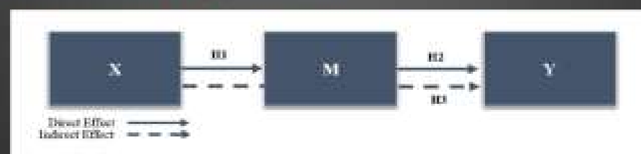
Including a Direct Effect Without Conceptual or Theoretical Justification.

- If the theory under investigation predicts complete mediation, than researchers should test a model that specifies complete rather than partial mediation.
- Omitting path c’ when complete mediation is hypothesized upholds the principle of parsimony and yields an estimate of path b that is consistent with the specified model

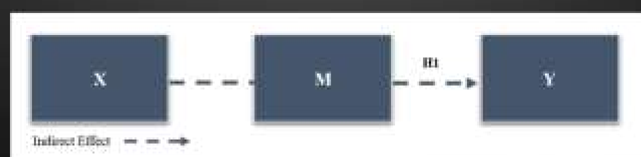
MEDIATION SOLUTION 4

- Two approaches for theorizing mediation effect:

- **i) *Segmentation Approach***



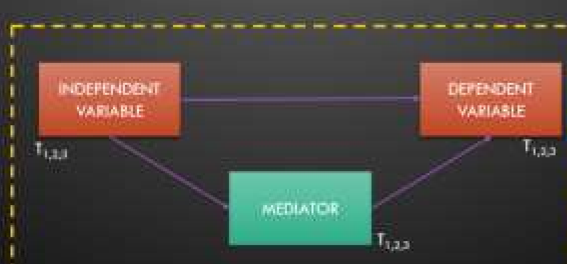
- **ii) *Transmittal Approach***



MEDIATION PROBLEM 5

Testing Mediation with Cross-Sectional Data

- Mediated models contain causal paths that inherently involve the passage of time
- Testing these path produce biased estimates
- Sequential/Longitudinal data can ameliorated these bias



MEDIATION SOLUTION 5

- Mediated models contain causal paths that imply the passage of time.
- When possible, assess mediation using longitudinal data, preferably with panel models that allow the comparison of alternative causal flows.
- Implement an experimental design to provide evidence of mediation (Eden, Stone-Romero, & Rothstein, 2015)

MEDIATION PROBLEM 6

Lack of attention to measurement error

- There is a belief that variables are measured objectively and error-free given reporting requirements and standards for publicly traded corporations (Dalton & Aguinis, 2013, ORM)
- Measurement error in X and M can bias path estimates upward or downward.
- Statistical tests of these paths can be either too liberal or too conservative either of which would lead to incorrect conclusions.
- In mediation tests using regression, measurement error is effectively disregarded.

MEDIATION SOLUTION 6

- Researchers should create and use more reliable measures.
- Use multiple-item measures for all constructs.
- Some effects of measurement error can be offset by using structural equation modeling (SEM) with latent variables
  - Increasingly prevalent
  - Not a magic cure for issues with poor quality measures
  - Only corrects for certain sources of measurement error

MODERATION

MODERATION PROBLEM 1

Lack of attention to measurement error: reliability of interaction term

- The reliability of an interaction term is a joint product of the linear terms' reliabilities and their covariance (Busemeyer & Jones, 1983; Cohen et al., 2003).
- Impact of measurement error depends on where it occurs.
  - Measurement error in independent (X) and moderator (Z) variables introduces bias in unstandardized coefficient estimates.
  - Measurement error in outcome variable (Y) does not bias coefficient estimates, attenuates estimates of explained variance

MODERATION PROBLEM 1

Lack of attention to measurement error: reliability of interaction term

- Example: Moderating effect of switching cost on the relation between customer satisfaction and customer loyalty:

$$\rho_{xz.xz} = \frac{\rho_{xz}^2 + \rho_{xx}\rho_{zz}}{\rho_{xz}^2 + 1} \qquad \rho_{xz.xz} = \frac{0 + (0.7)(0.7)}{0 + 1} = 0.49$$

Busemeyer and Jones (1983)

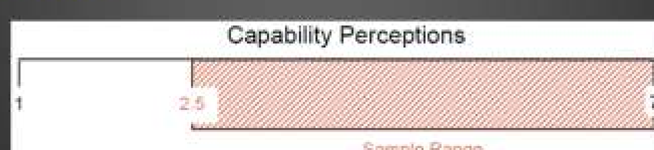
- Notably, if the correlation between X and Z is reduced to zero, then the reliability of the interaction term is the product of the reliabilities of X and Z.
- As Aguinis and Gottfredson (2010) illustrate, if the reliabilities of X and Z were each .70, then the reliability of the interaction term would be .49, which seriously limits the power to detect significant interactions (Cohen et al., 2003)

MODERATION SOLUTION 1

- Do not assume reliable measurement - this is typically a false assumption.
- Use measures that have high reliability
- Do not assume measurement error is zero and report the reliabilities of the measures (including the interaction term).
- Report reliability estimates for all predictors (including those hypothesized to play the role of moderator variables); this practice is particularly necessary when a hypothesized moderating effect is not found.
- This is especially important for situations when a hypothesized moderating effect is not found
  - If reliability of the predictors is low, an existing moderating effect is likely underestimated and may even go undetected (i.e., false negative).

MODERATION PROBLEM 2

Variable distribution are assumed to include the full range of possible values



- Statistical power for detecting moderating effects is diminished.
- Even if a moderating effect is statistical significant, range restriction can reduce the observed effect size.

MODERATION SOLUTION 2

- Attempt to capture the full range of scores of ALL variables included in the analysis.
- Use 7-point Likert scale (Dawes et al., 2008)
- If this is not feasible:
  i. provide the estimated population variance to rule out range restriction as plausible alternative explanation for the obtained results (i.e., non-significant and / or small moderating effects)
  ii. Use multiple indicators for when examine the interaction effect

MODERATION PROBLEM 3

Unequal sample size across moderator based categories

- This issue is akin to range restriction issues in continuous moderator variables

$$S_Z^2 = \frac{\sum(Z_i - \bar{Z})}{N-1} = \frac{Np(1-p)}{N-1}$$

N = 100

$n_1 = 50$, $n_2 = 50$, $p = 0.5$

$$\frac{(100)(0.5)(1-0.5)}{100-1} = 0.2525$$

$n_1 = 20$, $n_2 = 80$, $p = 0.8$

$$\frac{(100)(0.8)(1-0.8)}{100-1} = 0.1616$$

MODERATION SOLUTION 3

- Collect data such that the number of firms within each moderator based subgroup is similar (but keep in mind that this oversampling strategy may lead to an unrepresentative sample).
- Example- DV: Entry of Foreign Firm, IV: Media Coverage, & Mod = Type of Ownership

MODERATION PROBLEM 4

Insufficient Statistical Power

- Sample size is an important determinant of statistical power.
- With median N = 227.5 from a meta analysis conducted, this sample size is too small to yield statistical power of .80 or higher to detect the typical moderating effect size.
- Many moderating effects have likely gone undetected

MODERATION SOLUTION 4

- Statistical power is largely ignored
- A priori statistical power is necessary before collecting data to plan study design, and post hoc statistical power should be calculated in all cases when a moderating effect is not found to rule out the possibility that insufficient power has led to the no-moderator conclusion.
- Statistical Power can be increased by:
  - Conducting studies with larger sample sizes
  - Conducting research in settings that control for extraneous variables (i.e., experimental)

MODERATION PROBLEM 5

Artificial dichotomization of continuous moderator

- Artificial dichotomization occurs when researchers categorize continuous variables into groups (e.g., median split or mean split).
- Results in a loss of information.

MODERATION SOLUTION 5

- Artificial dichotomization:
  - Discard information
  - Reduces statistical power to detect moderating effect
  - Attenuates the size of the moderating effect
- Use of artificial dichotomization should be discontinued.

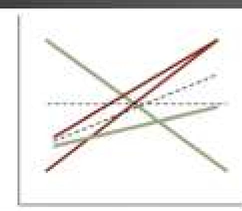
MODERATION PROBLEM 6

Presumed effects if correlation between product term and its components

- We often mean-center predictors and moderators for concern over multicollinearity issue.
- Any apparent multicollinearity created by the correlation of XZ with X and Z does not cause problems for test of moderation provided XZ, X and Z are modelled as predictors in the model.
- The test of moderation does not involve XZ in its raw form but rather the partialed XZ product which is necessarily uncorrelated with X and Z
- Nonetheless, centering predictors and moderators does facilitate interpretation of X and Z coefficients (i.2., the slope of each variable when the other equals zero.

MODERATION SOLUTION 6

- Mean centering is useful for interpreting lower-order coefficients as the average across values of the other predictor.



- When the interaction is ordinal, interpreting first-order effects may be informative
- However, this is not true for disordinal interactions

- Result regarding interaction effects remain unchanged if predictors are centered or not.

MODERATION PROBLEM 7

Interpreting First-order effects based on models excluding product terms

- X does not have a single unique effect on Y but a range of effects that varies according to the level of Z.
- It is not meaningful to hypothesize or test a single effect for a predictor when that predictor interacts with a moderator variable.

	Work Unit Performance	Work Unit Performance
	Model 1	Model 2
Informal Control Systems (ICS)	0.74*	-0.11
Task Interdependence (TI)		-0.11
ICS x TI		-1.12**

MODERATION SOLUTION 7

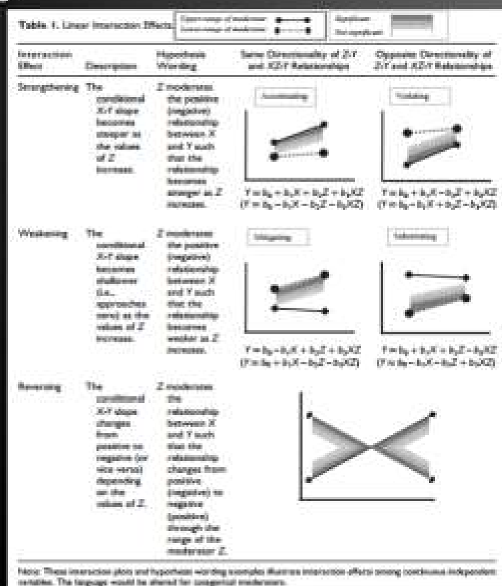


Table 1. Linear Interaction Effects.

Upper range of moderator / Lower range of moderator; Significant / Not significant

Interaction Effect	Description	Hypothesis Wording	Same Directionality of Z-Y and XZ-Y Relationships	Opposite Directionality of Z-Y and XZ-Y Relationships
Strengthening	The conditional X-Y slope becomes steeper as the values of Z increase.	Z moderates the positive (negative) relationship between X and Y such that the relationship becomes stronger as Z increases.	$Y = b_0 + b_1X + b_2Z + b_3XZ$ ($Y = b_0 - b_1X - b_2Z - b_3XZ$)	$Y = b_0 + b_1X - b_2Z + b_3XZ$ ($Y = b_0 - b_1X + b_2Z - b_3XZ$)
Weakening	The conditional X-Y slope becomes shallower (i.e., approaches zero) as the values of Z increase.	Z moderates the positive (negative) relationship between X and Y such that the relationship becomes weaker as Z increases.	$Y = b_0 - b_1X + b_2Z + b_3XZ$ ($Y = b_0 + b_1X - b_2Z - b_3XZ$)	$Y = b_0 + b_1X + b_2Z - b_3XZ$ ($Y = b_0 - b_1X - b_2Z + b_3XZ$)
Reversing	The conditional X-Y slope changes from positive to negative (or vice versa) depending on the values of Z.	Z moderates the relationship between X and Y such that the relationship changes from positive (negative) to negative (positive) through the range of the moderator Z.		

Note: These interaction plots and hypothesis wording examples illustrate interaction effects among continuous independent variables. The language would be altered for categorical moderators.

- Conclusions should be drawn from the full model that includes the predictor, moderator , and interaction term.
- Researchers should use simple slopes to test meaningful levels of the moderator variables.

SUGGESTED READINGS

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