

# A Tutorial on the Causes, Consequences, and Remedies of Common Method Biases



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February 24<sup>th</sup>, 2017

# A Work in Progress...



- Podsakoff, N.P., Podsakoff, P.M., & MacKenzie, S.B. A Tutorial on the Causes, Consequences, and Remedies of Common Method Biases.
- Based on, but extends and integrates, our previous work:
  - Podsakoff, P.M., MacKenzie, S.B., & Podsakoff, N.P. (2016). Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences. *Organizational Research Methods*, 19, 159-203.
  - Podsakoff, P.M., MacKenzie, S.B., & Podsakoff, N.P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 65, 539-569.
  - MacKenzie, S.B., Podsakoff, P.M., & Podsakoff, N.P. (2011). Construct measurement and validation procedures in MIS and behavior research: Integrating new and existing techniques. *MIS Quarterly*, 35, 293-334.
  - Podsakoff, P.M., MacKenzie, S.M., Lee, J., & Podsakoff, N.P. (2003). Common method variance in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88, 879-903.

# Agenda



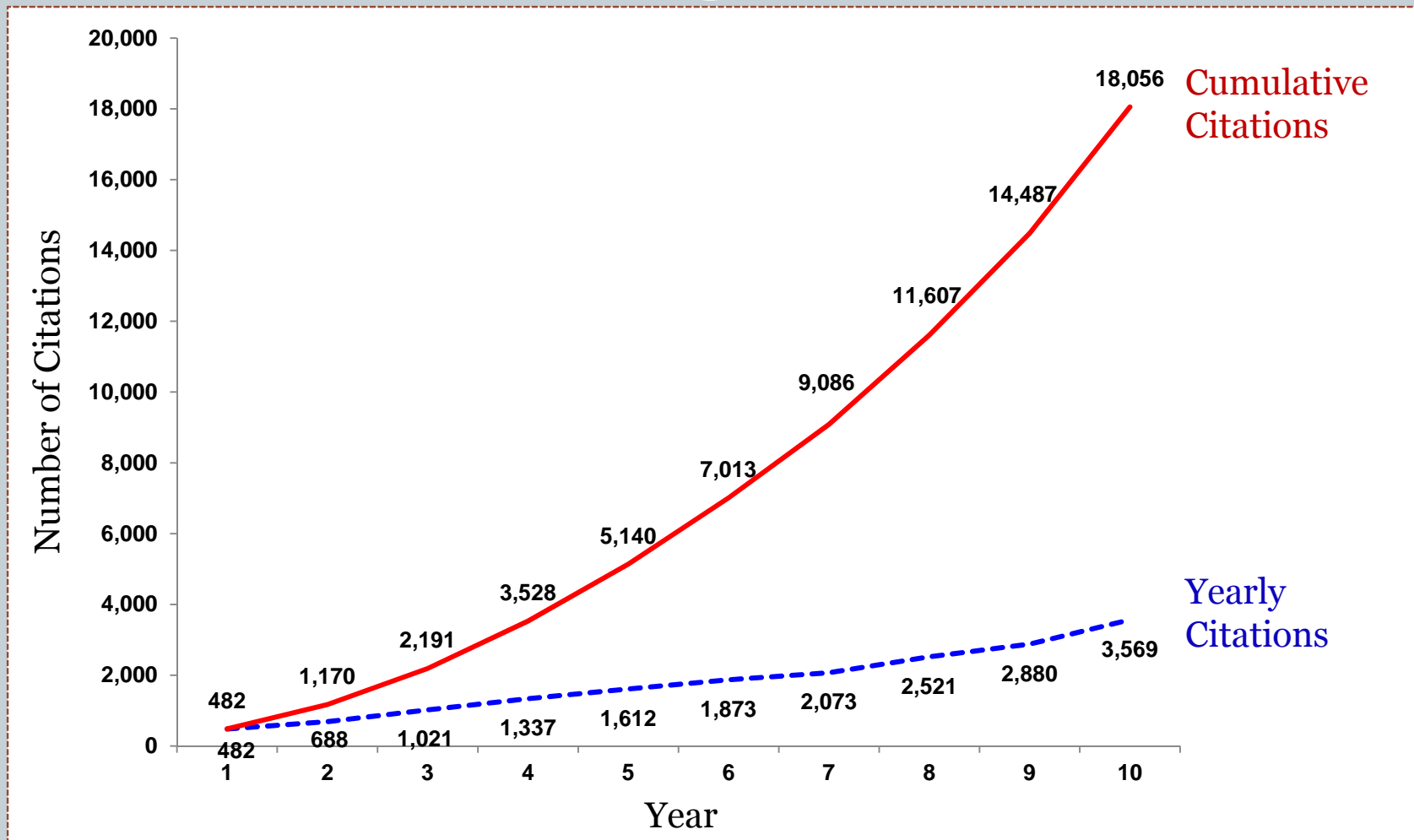
- **Definition of Key Terms**
- **Problems Resulting from Common Method Bias (CMB)**
  - Biased estimates of reliability and validity
  - Biased parameter estimates for relationships between constructs
- **Sources of CMB**
  - Source Characteristics
  - Item Characteristics and Context
  - Measurement Context
- **Integration of CMB and the Study Design Process**
  - Stages of the study design process
  - How procedural and statistical remedies fit into this process

# Why?



- The potential effects of CMB are *complex and not necessarily easy to understand*.
- Although there is debate, evidence continues to mount which demonstrates the *susceptibility of empirical relationships to CMB*.
- Training regarding common method biases is *rarely systematic or formalized*. We hope this tutorial provides a guide and tool.
- The sheer volume of research published on CMB is overwhelming, which seems to *result in multiple types of errors*:
  1. The overreliance on *post hoc, statistical* remedies to potential CMB, and
  2. The treatment of common method biases as a *unitary concept*, ignoring the fact that: (a) *multiple sources of method biases* may be present in a study, and/or (b) that remedies are often capable of *addressing some, but not all, of these sources*.

# Trends in CMB Article Citations (2007-2016)



Note. Figure reports citations to the six most impactful CMB articles.

# Definitions: Method



- “... the term *method* encompasses potential influences at several levels of abstraction. Taking a paper-and-pencil instrument as an example, these influences include the **content of the items, the response format, the general instructions and other features of the test-task as a whole, the characteristics of the examiner, other features of the total setting, and the reason why the subject is taking the test.** Two units that have any one of these elements in common can show convergence due to that source, so the **relationship obtained between them cannot safely be interpreted as associated with the traits or constructs in those units.**”
  - Fiske (1982, p. 82)
- This position is consistent with many (e.g., Bagozzi, 2011; Edwards, 2008; Messick, 1991), but not all (e.g., Lance et al., 2009).

# Definitions: (Common) Method Bias



- Bias means that an observed relationship deviates in some way from the “true” relationship; and *common method bias* refers to the type of deviation caused *by the similarity in methods used to obtain the data*.
- Common method bias, “exists when some of the **differential covariance among items [or constructs] is due to the measurement approach rather than the substantive latent factor.**” (Brown, 2006, p. 159)

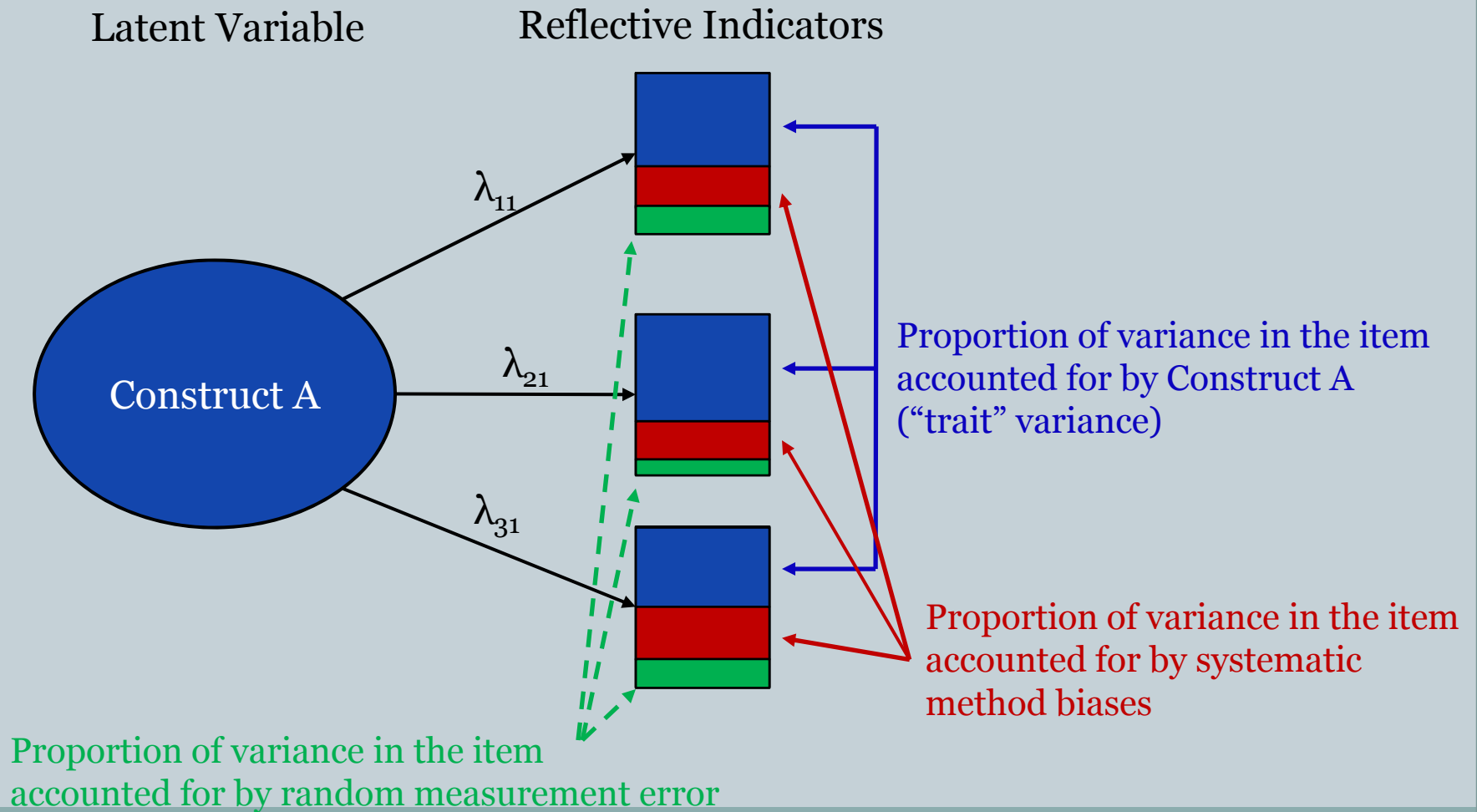
# Effects of Common Method Bias



- In general, there are two types of detrimental effects that biased covariation may cause for researchers:
  1. Biases the estimates of the **reliability and validity of a latent construct** (e.g., Bagozzi, 1984, Baumgartner & Steenkamp, 2001; Cote & Buckley, 1987; MacKenzie & Podsakoff, 2012; Podsakoff et al., 2012; Williams et al., 2010).
  2. Biases the estimates of the **empirical relationships between constructs**. Researchers (Baumgartner & Steenkamp, 2001; Cote & Buckley, 1988; Podsakoff et al., 2003; Siemsen et al., 2010) have demonstrated that when method factors are not controlled, they can **inflate or deflate** (or have no effect on) the estimates of the relationship between two constructs.

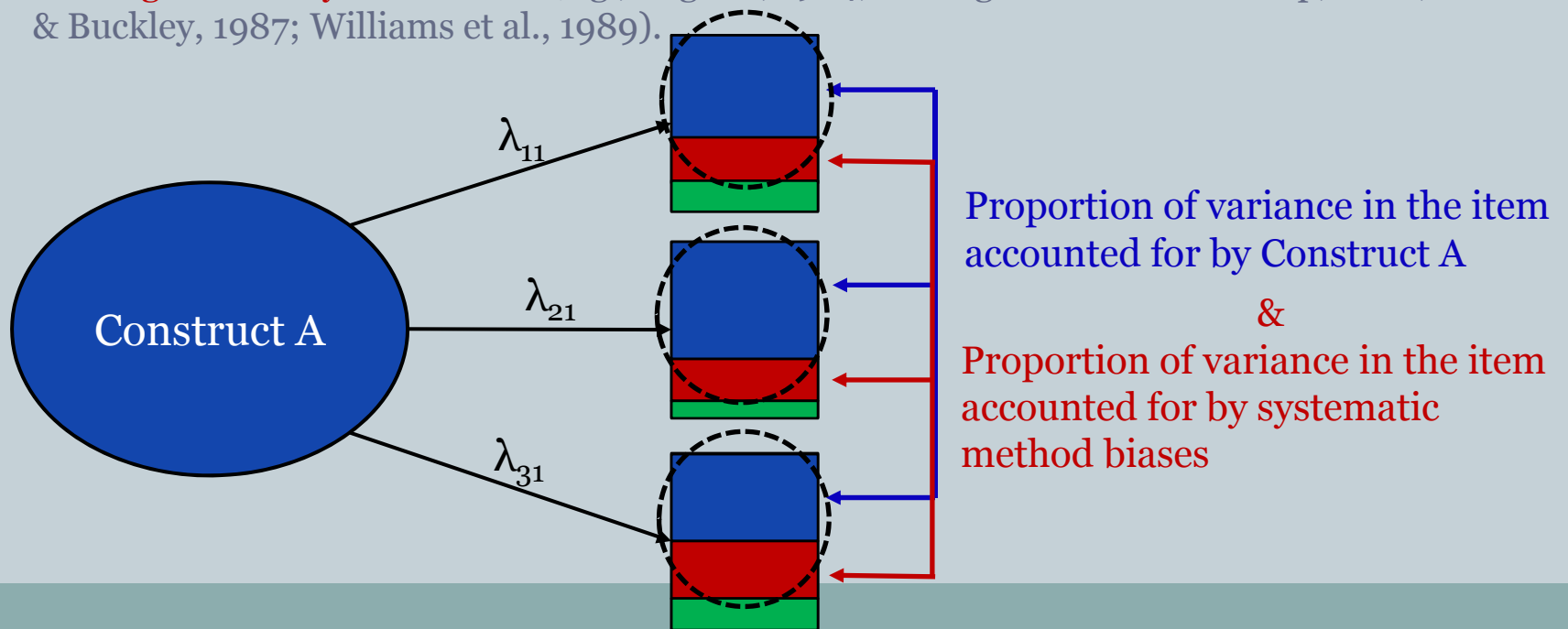


# A Measurement Model Illustration



# Bias in Reliability and Validity Estimates

- Reliability estimates, average variance extracted values (AVEs or  $\rho_{vc}$ ), and factor loadings are based on inter-item covariation. When these covariances are biased because a common method is used to obtain measures of the items, it can have several effects.
  - First, it can lead to incorrect conclusions about the **adequacy of scale reliability and convergent validity of the items** (e.g., Bagozzi, 1984; Baumgartner & Steenkamp, 2001; Cote & Buckley, 1987; Williams et al., 1989).



# Bias in Reliability and Validity Estimates (Cont.)



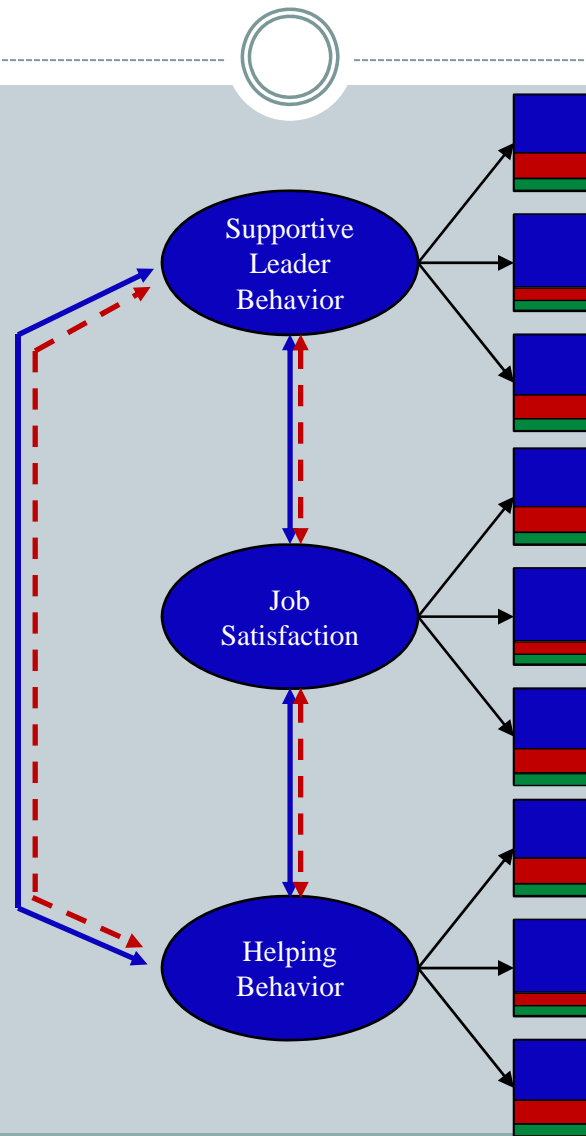
- Second, these biases can produce improper “corrected” correlations in meta-analyses (Le, Schmidt, & Putka, 2009). Since the corrected correlations used in meta-analytic studies are based on reliability estimates of the measures, these corrections will:
  - **Understate** the actual relationships between the focal (predictor and criterion) variables when the reliability estimates are **inflated**, and
  - **Overstate** the actual relationships between the focal variables when the reliability estimates are **attenuated**.
- Evidence from Multi-Trait Multi-Method Matrices (MTMM) analyzed using Confirmatory Factor Analytic (CFA) techniques indicates that approximately **18% to 32% of the total variance in the items is due to methods factors** (e.g., Cote & Buckley, 1987; Doty & Glick 1998, Lance et al., 2010; Williams et al., 1989).

# Bias in Parameter Estimates



- The second major problem with uncontrolled method factors is that they can **bias parameter estimates of the empirical relationships** between two different constructs.
- Several researchers (Baumgartner & Steenkamp, 2001; Cote & Buckley, 1988; Podsakoff et al., 2003; Siemsen et al., 2010) have demonstrated that method factors can **inflate, deflate, or have no effect on estimates** of the relationship between two constructs.

# A Structural Equation Model Illustration



# Bias in Parameter Estimates



- This leads to several other problems:
  - First, a researcher may conclude that a relationship exists when it does not (**Type 1 Error**) or that a relationship does not exist, when it does (**Type II Error**)
  - Second, estimates of the **amount of variance accounted for** in the criterion variable by the predictor variable may be either **under- or over-stated**.
  - Third, it can **enhance or attenuate the relationships between a focal construct and its antecedents, correlates, and consequences** and subsequently influence the inferences made about discriminant, nomological, and/or criterion-related validity.
  - All these problems may lead to **detrimental effects on the development and refinement of “theory”**; interpretation based on biased empirical findings may result in incorrect claims about the *proposed relationships, the mechanisms that connect constructs, and/or the boundary conditions for focal relationships*.

# Bias in Parameter Estimates



- Evidence from several studies indicates that method factors can bias the estimates of relationships between constructs.
  - Meta-analytic MTMM studies → True correlations between constructs were inflated between **38% and 92% by method bias**.
  - Meta-analytic “sub-groups” analysis → True correlations are **inflated from 133% to 304%** when predictor and criterion variables were obtained from the **same, compared to different, sources**.
  - Effects of response styles → **27% of the variance in the magnitude of correlations** between 14 consumer behavior constructs was attributable to five response styles.
  - Effects of item proximity → The correlation between items measuring unrelated constructs **increased by 225%** when they are **positioned next to each other compared to when they were positioned six items apart**.
  - Effects of item wording → correlation between constructs was **0.21** when item wording bias was controlled, but **0.50** when it was not controlled (**238% increase**).

Note. See Podsakoff et al. (2012, p. 545) for additional details on these studies.

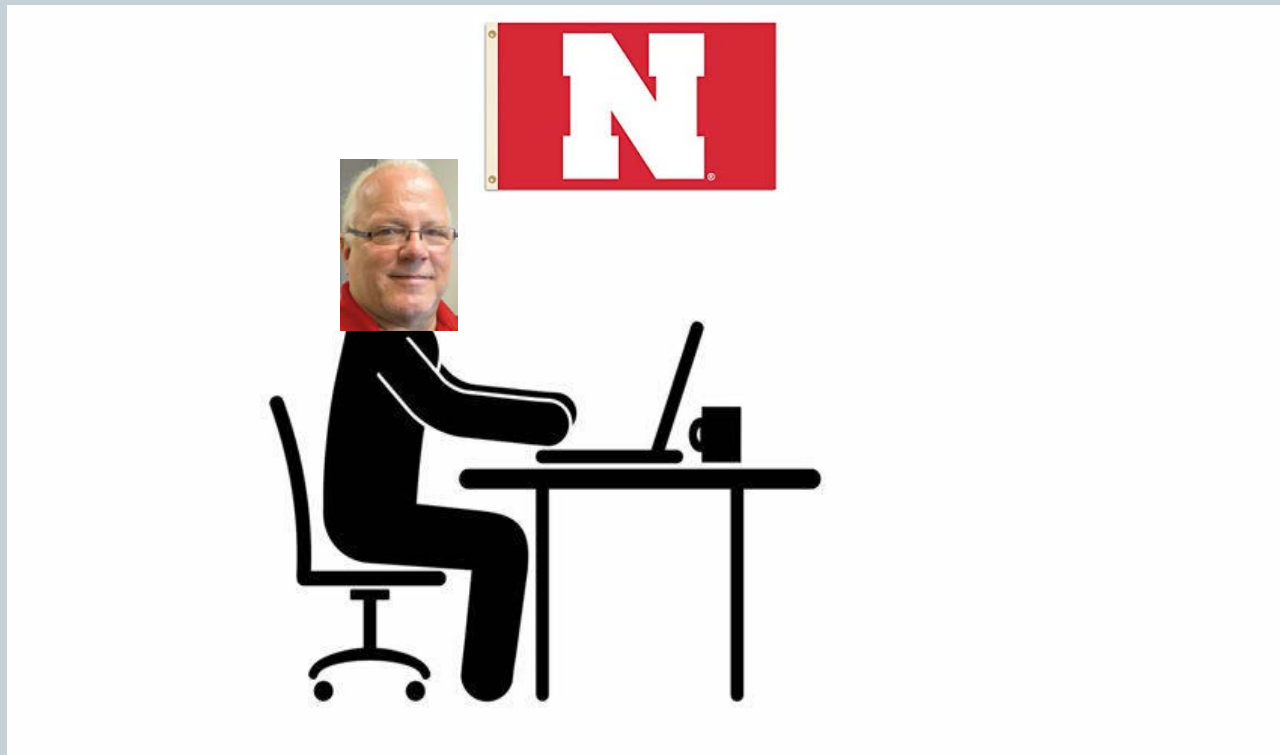
# Sources of Common Method Biases



- Consistent with our definition of *method as* encompassing “potential influences at several levels of abstraction”, there are multiple potential sources of common method biases (see Podsakoff et al., 2003).
  1. Rater Characteristics
  2. Item Characteristics
  3. Item Context
  4. Measurement Context



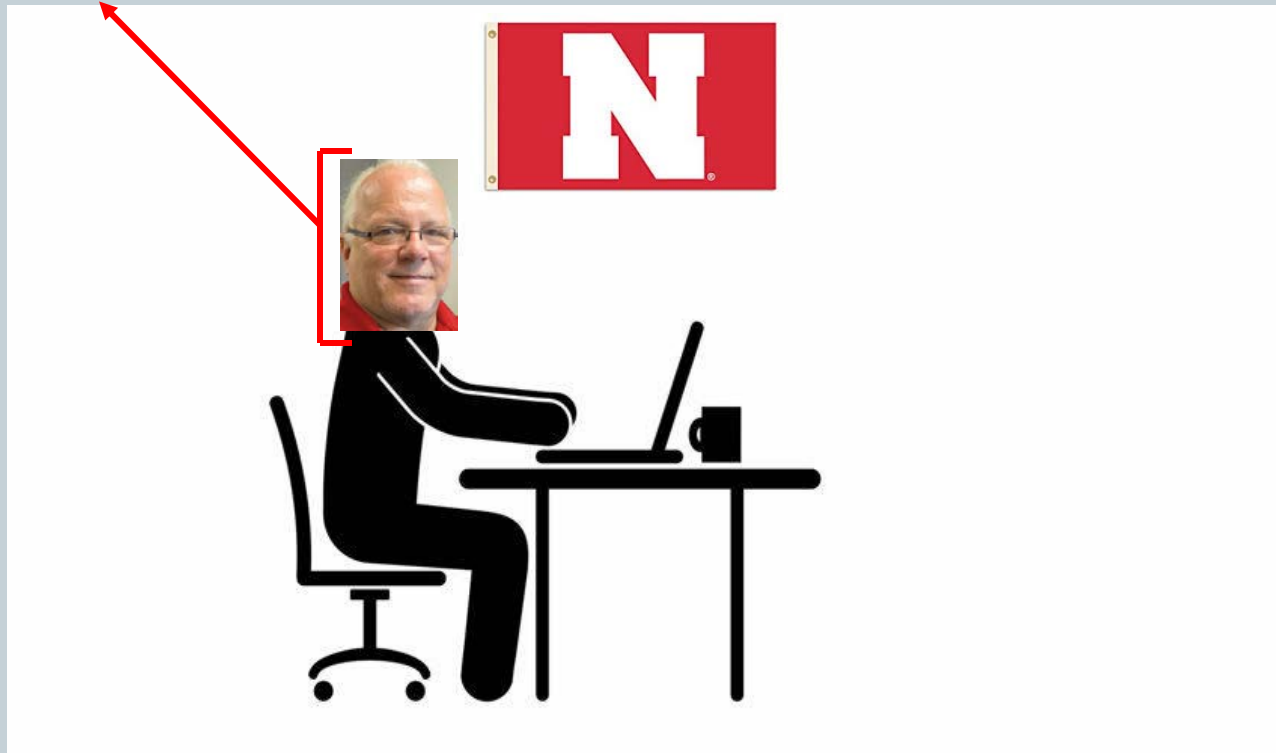
# An Illustration



# Rater Characteristics



## A. Rater Characteristics



# Rater Characteristics

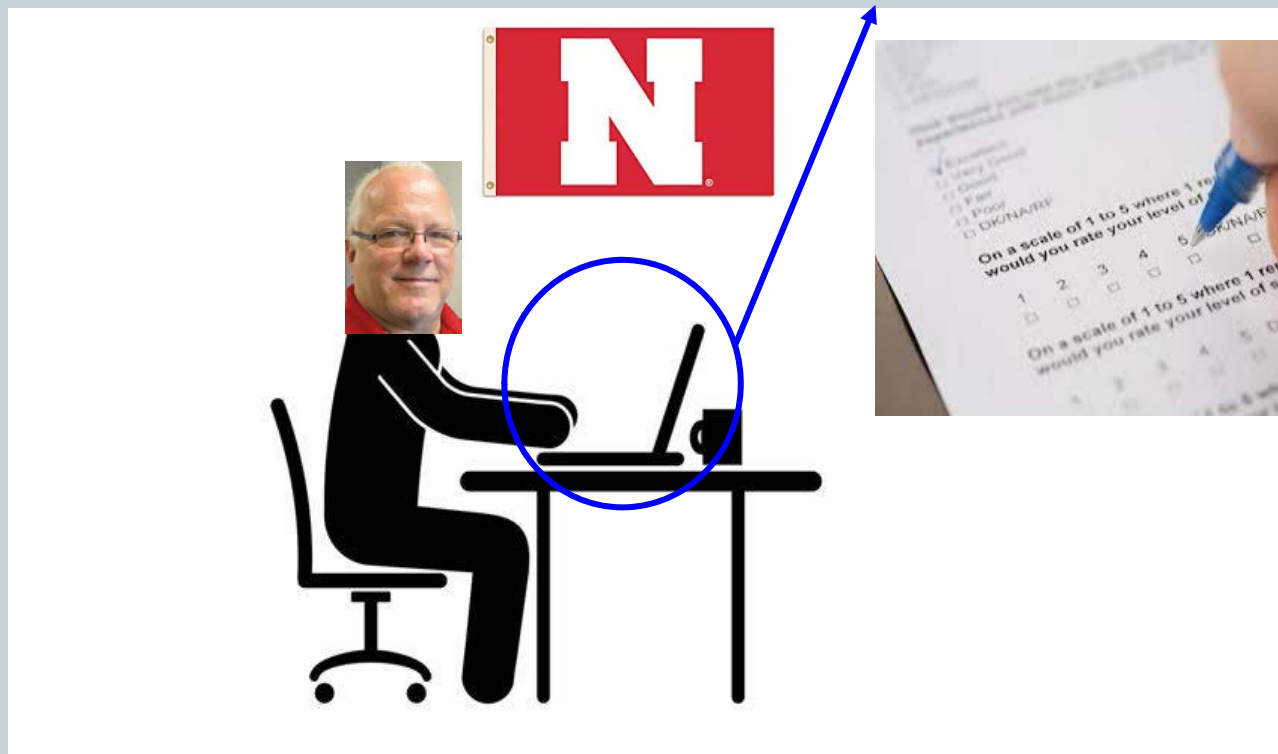


- Can result from the same respondent providing ratings of *the predictor and criterion variables (same source effects)*. In other words, when the same source provides ratings on multiple variables, the respondent's characteristics may serve as *confounds* that bias relationships between these variables.
- These characteristics include:
  - the **implicit theories** held by the rater;
  - a variety of **dispositional tendencies in their responding** (e.g., *consistency motifs; response styles such as acquiescent/leniency, disacquiescence/strictness, midpoint, or extreme; socially desirable responding*), and
  - both **trait and state forms of positive and negative affect**.

# Item Characteristics & Context



## B. Item Characteristics & C. Items Context



# Item Characteristics Effects



- The form in which items are *presented to respondents* may produce artifactual covariance in the observed relationships.
- “The assumption is generally made, and validated as well as possible, that what the test measures is determined by the content of the items. **Yet the final score of the person on any test is a composite of effects resulting from the content of the item and effects resulting from the form of the item used.** A test supposedly measuring one variable may also be measuring another trait which would not influence the score if **another type of item were used.**”
  - Cronbach (1946, pp. 475–476)

# Item Characteristics Effects



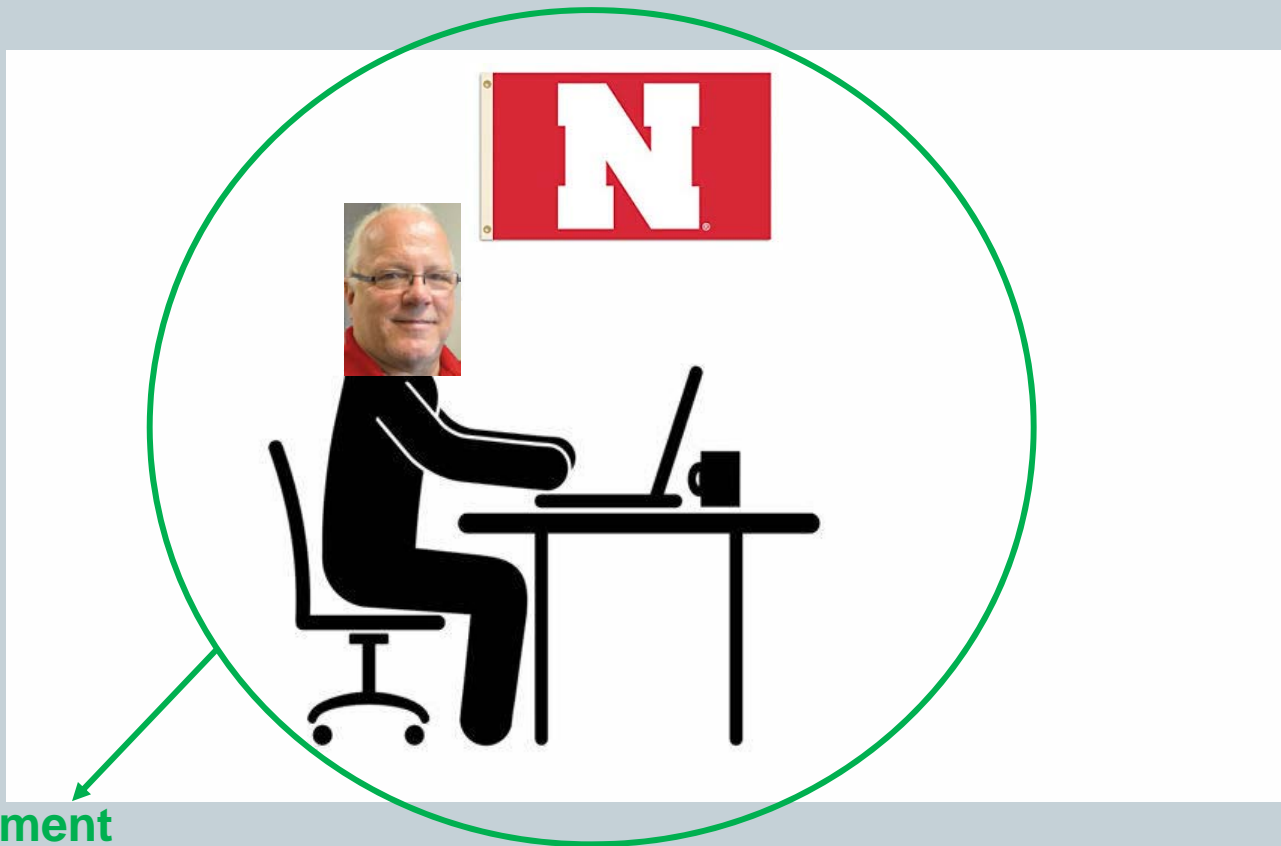
- Primarily, item characteristic effects may result when item content:
  - Elicits social desirable responding
  - Is ambiguous or vague, facilitating participants' idiosyncratic response styles
  - Is similar in terms of phrasing and/or framing:
    - ✦ Uses the same item stem or phrase (e.g., “At work today, ...” or “In general, my leader ...”)
    - ✦ Uses either positive or negative item wording (Lindwall, Barkoukis, Grano, Lucidi, Raudsepp, Liukkonen, & Thogersen-Ntoumani, 2012; Schmitt & Stults, 1985).
  - Is similar in terms of the options made available to raters to provide scores for each item, either in terms of **scale format** (e.g., Likert-type, frequency), and/or **the number** (e.g., 3, 5, 7, 9) **and content of scale anchors** (e.g., “strongly agree” or “agree”)

# Item Context Effects



- In addition to the content of the items, the context of the items can also elicit bias in multiple ways. More specifically, *item context effects* “refer to any influence or interpretation that a subject might ascribe to an item **solely because of its relation to the other items making up an instrument**” (Wainer & Keily, 1987, p. 187).
- These include biases that occur because of the **placement of an item(s)** in relation to other items (of the same and different constructs) in the questionnaire (*item priming, embeddedness, and positioning*), as well as the manner in which the **rater’s mood, fatigue, and/or recall is effected by item context**.

# Measurement Context



D. Measurement  
Context Effects



# Measurement Context Effects



- This refers to any artifactual covariation between measures that results from the *context or situation* in which the measures of the constructs are obtained. This includes obtaining the predictor and criterion variables:
  - At the same *point in time* → may facilitate consistency motif, implicit theories, and/or stylistic responding
  - In the same *location* → provide contextual cues for retrieval of information from long-term memory
  - Using the same *medium of measurement* → the specific medium (e.g., paper-and-pencil, online survey, phone interview) for gathering data may influence observed variable scores

# Potential Remedies: Procedural



- Now that we understand the potential problems and their sources, what *solutions* available to us?
  - We typically refer to a variety of “remedies”, which fall into a few different categories:
- Procedural Remedies
  - Obtain measures of the predictor and criterion from *different sources*
  - Separate measures of the predictor and criterion variables psychologically, temporally, or methodologically
    - ✦ Obtain measures of the predictor and criterion at *different points in time*
    - ✦ Use *different methods* to gather the predictor and criterion variables
  - Improve item content (e.g., reduce ambiguous content; avoid double-barreled questions)

# Potential Remedies: **Statistical**



- **Statistical Remedies**
  - Directly Measured Latent Method
    - ✦ Positive/Negative Trait Affectivity
    - ✦ Positive/Negative Affect or Mood State
    - ✦ Social Desirability
    - ✦ Impression Management
    - ✦ Response Styles (e.g., Acquiescence, Disacquiescence, Midpoint, Extreme)
  - Instrumental Variable
  - Marker Variable
  - Unmeasured Latent Factor Model
  - Harman's Single Factor Test

# Potential Remedies: **Statistical**



## Distinguishing Statistical Remedy Types

- **Statistical Remedies**

- Directly Measured Latent Method
- Instrumental Variable
- Ideal Marker Variable



### **“A Priori” Statistical Remedies**

- Requires explicit consideration during the study design process → a priori identification of appropriate measures
- Also requires statistical analyses

- Unmeasured Latent Factor Model
- Non-Ideal Marker Variable
- Harman’s Single Factor Test



### **“Post Hoc” Statistical Remedies**

- Requires no explicit consideration during the study design process → no a priori identification of measures
- Relies solely on statistical analyses

Note. The manuscript focuses on the most popular remedies; a more complete review of additional remedies is provided in Podsakoff et al. (2003, 2012).

# The Problem with Remedies



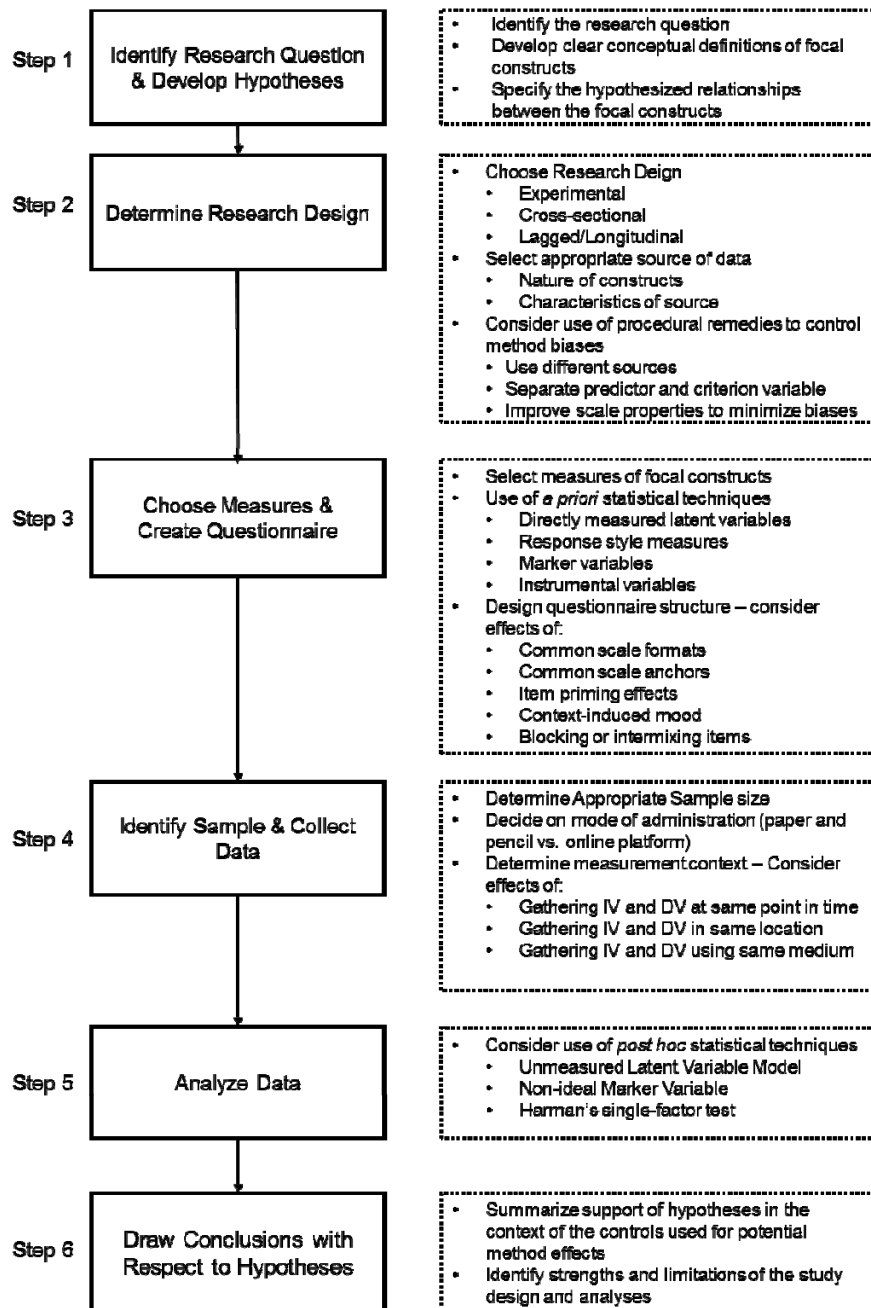
- In our experiences, we have noted two prevalent problems when researchers are attempting to “remedy” potential common method biases present in their empirical data:
  - The **overreliance on *post hoc* statistical procedures**, which are subject to several limitations, and *do not demonstrate that researchers have given adequate forethought* to this issue when designing their study.
  - The treatment of common method biases as a **unitary concept with a one-remedy-solves-all-problems** perspective; this approach does *an inadequate job of considering multiple sources of potential method bias that may be present*, and the limitations of various remedies

# Method Bias and the Study Design Process



- To address these concerns, we have attempted to more effectively **integrate specific considerations and decisions regarding common method biases** directly into an **multi-stage overview of the study design process** for organizational researchers.
- We hope that this tutorial will help researchers and reviewers better understand:
  - How decisions made during the study design process **affect the likelihood and impact of specific sources of common method biases**; and
  - The **strengths and limitations of several procedural and (both a priori and post hoc) statistical remedies** for addressing specific sources of common method biases.

## Overview of the Study Design Process



## Caveats

1. Based on the hypothetico-deductive model.
2. We focus on research designs that use some form of questionnaire.
3. Not comprehensive, nor exhaustive, with respect to all research design issues.
4. Practical limitations may prevent a researcher from engaging in all suggested practices.
5. Our “Study Design” process also includes analyzing the data that is collected.

# Step 1: Research Question & Specify Hypotheses



1. Develop and articulate a good research question(s).
2. Provide clear conceptual definitions of the focal constructs and the nature of the relationships between them.
  - Podsakoff, MacKenzie, & Podsakoff (2016, ORM)
3. Formally specify hypotheses about the nature of the relationships between the focal constructs.



## Step 2: Determine Research Design



- “The function of a research design is to ensure that the evidence obtained enables us to **answer the initial [research] question as unambiguously as possible.**”
  - deVaus (2001, p. 9)
- “**The main function of research design is to *control variance*.** A research design is, in a manner of speaking, a set of instructions to the investigator to gather and analyze his data in certain ways. It is therefore a control mechanism. The statistical principle behind the mechanism ... is: ***Maximize systematic [trait] variance, control extraneous systematic [method] variance, and minimize error variance.*** In other words, we *must* control variance.”
  - Kerlinger (1973, p. 306)

## Step 2: Determine Research Design



1. Does the design facilitate an adequate answer to the research question and/or hypotheses?
2. Does the design permit the researcher to infer that a **causal relationship** exists between the presumed IV and DV?
  1. Empirical association between IV and DV
  2. Temporal precedence (IV precedes the DV in time)
  3. Rule out alternative (3<sup>rd</sup> variable) explanations for the observed association between variables
3. Does the design allow the researcher to **generalize** the findings to other individuals, tasks, settings, and measures?

# Step 2: Determine Research Design



## 1. Select an appropriate design:

### 1. Experimental

1. Laboratory experiment
  2. Field experiment
  3. Quasi-experimental
- } Procedurally controls for trait and state rater effects (through random assignment) and can provide strong causal inferences.

### 2. Non-experimental

1. Cross-sectional field survey
  - Highly susceptible to CMB through rater, item characteristics & context, and measurement context (time & method) effects
2. Lagged/longitudinal survey } Procedurally controls for state-based rater characteristics, and can help improve the strength of causal inferences.

# Step 2: Determine Research Design



## 2. Select an Appropriate Source for Each Construct

- Identify sources in *the best position* (i.e., has the **ability, motivation, and opportunity**; Podsakoff et al., 2003, 2012) to provide accurate responses to the items
  - ✦ Peers/Coworkers
  - ✦ Supervisors/Managers/Leaders
  - ✦ Subordinates/Direct Reports
  - ✦ Spouses/Significant Others
  - ✦ Self-reports (Note: not synonymous with same source or common method bias; Podsakoff, Whiting, Welsh, & Mai, 2013)
  
- When measures of the *predictor and criterion variables are obtained from different sources*, researchers can reasonably infer that this serves as a **procedural control** for **rater characteristics** as a source for CMB
  - ✦ See Kammeyer-Mueller, Steel, & Rubenstein (2010) for a different perspective

## Step 3: Choose Measures and Create Questionnaire



1. Select Measures of Focal, Hypothesized Constructs
2. Select Measures of Potential Confounds
3. Select the Content, Format, and Structure of the Questionnaire

## Step 3: Choose Measures and Create Questionnaire



- **Step 3a: Select Measures of Focal, Hypothesized Constructs**
  - First, identify measures that **adequately capture the conceptual definition of the construct** (limiting *deficiency* and *contamination*)
  - Second, measures should have demonstrated **adequate psychometrics** (e.g., *reliability*, *factor structure*, etc.)
  - Third, measures should be **distinguishable from other, related constructs** (i.e., have *discriminant validity*)
  - Fourth, reconsider items with **obvious socially desirable content**

Note. See Podsakoff, MacKenzie, & Podsakoff (2016) and MacKenzie, Podsakoff, & Podsakoff (2011)

## Step 3: Choose Measures and Create Questionnaire



### • Step 3b: Select Measures of Potential (Methods) Confounds

#### ○ Directly Measured Latent Variable(s)

- ✦ Positive/Negative Trait Affectivity
- ✦ Positive/Negative Affect or Mood State
- ✦ Social Desirability
- ✦ Impression Management
- ✦ Response Styles (e.g., ARS, DRS, MRS, ERS)

“Direct” Measures Designed to Control for *Specific* Sources of CMB

#### ○ Instrumental Variable

#### ○ Ideal Marker Variable

“Indirect” Measures Designed to Control for CMB *In General*

- It is critical to consider this now – highly unlikely that a researcher can go back to gather this data later (“**fatal flaw**”)

## Step 3: Choose Measures and Create Questionnaire



- The “Ideal” Marker Variable Approach
  - A marker variable serves as an indirect surrogate for method biases in general; the marker variable should be selected carefully, the measures obtained from survey participants, and then included in the analyses.
  - Requirements
    1. *A priori* selection (when selected post hoc, referred to as a *non-ideal marker*).
    2. Select measures that reflect an underlying construct that has **no conceptual relationship** with the substantive variables.
    3. An ideal marker variable should **share the same “method characteristics”** (*content* and *format*) as the substantive measures under examination.

Note. See Lindell & Whitney (2001); Richardson et al. (2009); Williams et al. (2010) for more information on requirements.



## Step3: Choose Measures and Create Questionnaire



- Step 3c: Select the Content, Format, and Structure of the Questionnaire
  - Researchers should consider the *collective content* of the survey, the *format* of the survey, and the *structure* of the survey.
    - ✦ Item proximity (Weijters et al., 2009, 2014)
      - Blocking items → **increases** *reliability* and *convergent item validity (AVE)*, and **decreases** inter-construct correlations
      - Intermixing items → **decreases** *reliability* and *convergent item validity (AVE)*, and **increases** inter-construct correlations
    - ✦ Reconsider scales with common properties:
      - Shared *item content* inflates correlations (Dalal, 2005; Spector et al., 2010)
      - Shared *response formats* inflate correlations (e.g., Arora, 1982; Kothandapandi, 1971; Podsakoff et al., 2013, JAP)
      - *Positively and negatively worded item* content can produce distinct method factors (Lindwall et al., 2012; Schmitt & Stults, 1985)

## Step 4: Collect Data



- Researchers should select an **appropriate sample** from which to collect data. At the least, the sample should:
  - Be *adequately accessible* to the researchers
  - Have the *ability to understand the level* at which content is presented (if item content is too difficult for participants to understand, it increases the likelihood they will engage in stylistic responding)
  - *Demonstrate variance* on the focal constructs under examination
- Regarding potential CMB, researchers should consider the **country/culture** of the sample.
  - Several studies have shown that *specific countries or cultures tend to exhibit stylistic responding* that differs from other countries or cultures
    - ✦ See Yang, Harkness, Chin, and Villar (2010) and Van Vaerenbergh and Thomas (2013) for reviews

## Step 5: Analyze Data



- Researchers can use a variety of statistical techniques (e.g., *ANOVA*, *regression*, *latent variable measurement and structural models*) to test their hypotheses
- In addition, a variety of measures representing the “**a priori statistical**” approach could be included in the analyses
- Finally, researchers could also implement “**post hoc statistical**” techniques
  - Recent research has identified *several limitations* inherent with the purely **post hoc techniques**

## Step 5: Analyze Data (cont.)



- Return to the **Ideal Marker Variable** Example from Step 3
  - *Correlation-* and *regression-based* techniques have received criticism (Richardson, Simmering, & Sturman, 2009; Podsakoff et al. 2003, 2012; Williams, Hartman, & Cavazotte, 2010; Williams & O'Boyle, 2015)
  - In response, Williams and colleagues (2010) have worked to develop and test a *latent marker variable technique*

## Step 5: Analyze Data (cont.)



- Williams et al. (2010) propose a three-phase confirmatory factor technique to identify and control for method bias.
  - **Phase I:** The presence and impact of method effects associated with the marker variables are examined by specifying **five different latent variable models** (with *constraints to factor loadings and latent variable correlations added and removed*) and **comparing their relative fit to each other.**
  - **Phase II:** The analysis is focused on quantifying how method variance affects the reliability of the substantive constructs, and **decomposes their reliability into the portion due to the substantive construct versus the method factor.**
  - **Phase III:** Perform a **sensitivity analysis** to determine the *robustness* of the results to **increasing amounts of method variance** associated with sampling error in the indicators. (*Test alternative values* derived from confidence intervals from previous models).

Note: See also Richardson, Simmering, & Sturman (2009); Williams & O'Boyle (2015).

# Step 6: Interpret Results



- Step 6: Interpret Results in the Context of Research Questions/Hypotheses
  - Summarize the (lack of) support of hypotheses provided by the results of analyses designed to control for potential method biases
    - ✦ Highlight the effect of the sources that were controlled
  - Accurately identify the strengths and limitations of your study design and analytic techniques
    - ✦ Recommend how future research can address the limitations present in a study

# Closing Comments



- This was a necessarily brief summary of the effects, sources, and remedies for common method biases.
  - The paper provides much more information on the *strengths and limitations of both statistical and procedural remedies*, and demonstrates how *considerations for sources of and remedies for CMB* should be integrated into the study design process
- Moving forward, researchers should:
  - Reconsider the **overreliance on post hoc statistical remedies**
  - Reconsider the **“one-remedy-addresses-all-sources”** approach to CMB
  - Consider all the **potential sources of CMB** when designing a study, and take an *a priori approach* to remedying CMB

# Coauthors on CMB Research



I want to recognize and thank all of the coauthors who have worked with me on common method bias research over the past 15 years.

**Jeong-Yeon Jay Lee**

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**Ke Michael Mai,**

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**Philip M. Podsakoff**

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**Thank you!**

**Feedback and Questions?**