Conceptualizing Variables: Problems and Solutions

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Problems with formative and higher-order reflective variables

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ABSTRACT

Cadogan and Lee (this issue) discuss the problems inherent in modeling formative latent variables. In response to the commentaries by Rigdon (this issue) and Finn and Wang (this issue), the present study argues that regardless of whether statistical significance is achieved, researchers are unable to illuminate the nature of a formative latent variable. Second, issues regarding formative indicator weighting, highlighting that the weightings of formative indicators can be specified as part of the construct definition. Finally, the study shows that higher-order reflective constructs provide recommendations on a number of alternative models which should be used to test the formative model.)
Conceptualizing Variables

General purpose of this talk:

- To demonstrate some errors inherent in using popular variable forms in conceptual models.

- To provide guidance on best practice.

Why?
A Dip into the Literature


Diamantopoulos et al. (2008), “Advancing formative measurement models,” Journal of Business Research

A Dip into the Literature


A Dip into the Literature


\[ x_i = \lambda_i \xi + \delta_i \]
Latent variable with formative indicators

This model is inherently multidimensional

\[ \eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta \]

Wells et al. (2011) MIS Quarterly

Web site quality

Dimensions

SEC: Security

DD: Download Delay

NAV: Navigability

VAP: Visual appeal

WSQ

SEC

DD

NAV

VAP

x1 x2

x3 x4

x5 x6
Problems with the formative variable model:

\[ \eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta \]

1. Entity realism:

Since Eta (\( \eta \)) is defined as a composite:

Then *Eta is not a real separate entity from the indicators that define it.* Eta has no meaning of its own.

Eta is vague and imprecise, conceptually.
Problems with the formative variable model:

$$\eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta$$

2. The $\gamma$s are not causal relationships.

*Eta is not a real separate entity from the indicators that define it:*

Cause and effect requires a cause and an effect (i.e., two separate entities).

The gammas are simply weights to be defined by the researcher. NOT estimated.

Different weights = different Eta variable.
Problems with the formative variable model:

\[ \eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta \]

3. Eta should not be used as a variable in a structural model.

*Eta is not a real separate entity from the indicators that define it:*

For instance, if anything exogenous causes variance in Eta, it must operate through the indicators.
Illogical model: antecedent modeled as antecedent to formative variable

\[ \xi_1 = \text{Antecedent latent variable with reflective indicators } x_1, x_2 \text{ and } x_3 \]

\[ \eta = \text{Formative variable} \]

\[ x_4, x_5, x_6 = \text{Formative indicators} \]
\( \xi_1 = \) Antecedent latent variable with reflective indicators \( x_1, x_2 \) and \( x_3 \)

\( \gamma_1, \gamma_2, \gamma_3 = \) Observed formative indicators

\( \eta = \) Composite variable

\( \zeta_2, \zeta_3, \zeta_4 = \) Antecedent latent variable with reflective indicators

\( \delta_1, \delta_2, \delta_3 = \) Error terms

\( \lambda_1, \lambda_2, \lambda_3 = \) Loadings

\( \xi_1 \) is modeled as a latent variable with reflective indicators \( x_1, x_2, x_3 \). The indicators are measured and cause the latent variable. The model includes formative indicators \( y_1, y_2, y_3 \) that are observed and influence the latent variable \( \eta \). Error terms \( \delta_1, \delta_2, \delta_3 \) represent the unexplained variance in the indicators. Loadings \( \lambda_1, \lambda_2, \lambda_3 \) measure the strength of the relationship between the latent variable and its indicators. The composite variable \( \eta \) is influenced by the formative indicators and is defined with error terms \( \zeta_2, \zeta_3, \zeta_4 \).
Endogenous formative measures - examples

Iacouvou et al. 2009. Selective status reporting in information systems projects: a dyadic-level investigation. MIS Quarterly


Dowling 2009. Appropriate audit support system use: the influence of auditor, audit team, and firm factors. Accounting Review

Im & Rai 2008. Knowledge sharing ambidexterity in long-term interorganizational relationships. Management Science

Industry tenure

H: (+) but ns

(-) & sig.

Supply chain contagion

Information exchange

 Recommending

 Promises

 Threats

 Ingratiation

 Inspirational appeals

ζ1=0

Environmental uncertainty

H: (+), find (+) & sig

Supply chain contagion

None are sig.

Information exchange

Recommending

Promises

Threats

Ingratiation

Inspirational appeals

ζ₁=0
Exogenous formative variable

Exogenous formative variable: MIMIC model

\[ \eta_1 = \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 \]
\[ \eta_2 = \gamma_4 \eta_1 \]
\[ y_1 = \lambda_1 \eta_2 + \delta_1 \]
\[ y_2 = \lambda_2 \eta_2 + \delta_2 \]
\[ y_3 = \lambda_3 \eta_2 + \delta_3 \]
\[ y_4 \]
\[ y_5 \]


**Exogenous formative variable: MIMIC model**

\[ y_1 = \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \eta_1 \]

\[ y_2 = \lambda_1 \eta_1 + \lambda_2 \eta_2 + \lambda_3 \eta_3 + \delta_3 \]

\[ H_1 = \text{Common factor underlying } y_4 \text{ and } y_5 \]

Possible causes of $\eta_1$
Higher-order reflective models

Reflective 2nd-order
Latent variable = \( \xi_1 \):
\( \eta_1 \), \( \eta_2 \) and \( \eta_3 \),
are reflective 1st order latent variables
CON: Convenience
ENV: Environment
QP: Quality of Products
QS: Quality of Services
Multi-item reflective measures revisited:

- Measures represent a single dimension (describe the same single entity).

- And are conceptually interchangeable (can remove a measure with no loss of meaning – are redundant).

- They do not capture unique facets of construct (a single dimension is unidimensional).
Higher-order reflective models

\(\eta_s\) reflect a unidimensional construct \((\xi_1)\)

Higher-order model is redundant.
Alternatives to higher-order reflective models

ηs are distinct constructs – there is no unidimensional variable that they reflect

Model the ηs separately.
Alternatives to higher-order reflective models

If the aim of modeling higher-order reflective constructs is to simplify the model, then a formative approach might make sense.

However, remember that you should not use formative variables as endogenous, and there are also problems with using them as exogenous.

Model the $\eta$s separately.
What are higher-order reflective models?

ηs discriminate and are different constructs

ξ1 an unmeasured antecedent; or contains other reasons for shared variance between ηs.

ξ1 = Unmeasured antecedent to the ηs.

Model the ηs separately.
What are higher-order reflective models?

ηs discriminate and are different constructs

ξ1 could be hiding causal relationships between the ηs.

Model the ηs separately.
Implications

If it’s Multidimensional
Think again

Stronger models will emerge

More realistic recommendations