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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 as endogenous. In response to the commentaries by Rigdon (this issue) and Finn and Wang (this issue), the present article extends the discussion on formative measures. First, the article shows that regardless of whether statistical identification is achieved, researchers are unable to illuminate the nature of a formative latent variable. Second, the study clarifies issues regarding formative indicator weighting, highlighting that the weightings of formative components should be specified as part of the construct definition. Finally, the study shows that higher-order reflective constructs are invalid, highlights the damage their use can inflict on theory development and knowledge accumulation, and provides recommendations on a number of alternative models which should be used in their place (including the formative model).

1. Introduction

The invited commentaries by Rigdon (this issue), and Finn & Wang (this issue), on the paper, "Improper Use of Endogenous Formative Variables (IFV)," (Cadogan and Lee, this issue). are greatly appreciated. Both comments throw important light on significant problems in contemporary understanding of the formative model and in current measurement practices in business research. The current authors share with Rigdon and with Finn and Wang a desire to expand understanding of measurement theory, and to make a positive impact on the application of measurement by practicing business researchers.

Nevertheless, the commentaries contain a number of important points that require counter comment or elaboration. The goals of the present paper are threefold. First, to re-examine the original intentions behind *IFV*, and in so doing, place a variety of Rigdon's comments in context, demonstrating that he is in agreement with the current authors in many places. In particular, the current paper clarifies why one can never know how a formative *latent* variable varies — regardless of statistical identification issues. Second, building on Rigdon's comments, the current paper demonstrates that, for formative variables to have utility in theoretical models, the loadings of the formative indicators should be specified as part of the construct definition prior to any analysis. Third, while the current authors share a number of important views with Finn and Wang, the authors show that the idea of a higher-order reflective construct makes no conceptual sense, and that the latter's use impedes theory development efforts and knowledge accumulation.

2. Response to Rigdon

Rigdon's commentary on *IFV* provides some important points which help make the case that *IFV* presents even stronger. In fact, in essence, Rigdon agrees entirely with the key message underpinning *IFV* — that researchers should not model antecedents to formative variables at the construct/aggregate level. Instead, antecedents should be modeled at the individual formative item level. However, a number of aspects of Rigdon's commentary require clarification.

2.1. Equations versus pictures

First, Rigdon argues that *IFV* exhibits a 'lack of application of basic mathematics', since the arguments could be expressed using mathematical equations. The authors agree with Rigdon, to the extent that a purposeful attempt is made to ensure that *IFV* is accessible to those who are not mathematically inclined. For better or worse, many applied researchers – those who go about the day-to-day business of creating and using measures – are more comfortable with diagrammatic representations of models.

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2.2. It's too obvious, so why bother?

Second, Rigdon implies that the key thesis of *IFV* (that it is wrong to use formative endogenous variables) is self-evident, and so questions the need to explain the problem. Yet, in practice and in prestigious journals, applied researchers commonly model formative variables as endogenous (e.g., Dowling, 2009; Hoetker & Mellewigt, 2009; Jarvis, MacKenzie, & Podsakoff, 2003; Klein & Rai, 2009; van Riel, Berens, & Dijkstra, 2009; Verhoef & Leeflang, 2009). As such, whether or not the illogical nature of formative endogenous variables is ‘obvious’, there is clearly a need to clarify the issues for researchers.

2.3. Can one ever know how a formative latent variable varies?

Third, Rigdon suggests that *IFV* ‘errs’ in some way ‘when discussing issues of identification’. Rigdon states that the authors ‘assert repeatedly that if a formatively measured construct has a structural error term with a free structural variance and no reflective indicators, then the construct's total variance is not identified’. Rigdon notes that such a model *would* be statistically identified with the addition of two or more exogenous constructs. Of course, Rigdon is correct: such a model would be identified.

However, the possibility of statistical identification should not be taken to invalidate the claim in *IFV* that one can never operationally use a formative latent variable in an empirical study. Researchers should not be misled into thinking that achieving statistical identification allows one to obtain information about the variance of a formative latent variable.

Accordingly, the authors take the current opportunity to reframe their logic using a fictitious example to demonstrate the impossibility of determining the variance of a formative *latent* variable. Fig. 1a shows a formative latent variable model and, following Rigdon, socioeconomic status (SES) is chosen as the variable of interest. In the example, SES ($\eta1$) is defined by three formative indicators: education (x1), job prestige (x2), and income ($\zeta1$). Note that the formative variable is latent because in a fictitious data set, data on income is not available. Thus, the conceptual model of SES contains two observed formative indicators (job status and education) and one unobserved formative indicator, income (which is represented by an error term, $\zeta1$). In *IFV* the authors explain that the formative latent model is useful as a conceptual tool, potentially, but operationally it is incomplete: that is, the $\zeta1$ term represents an operational error (variable(s) that have not been measured) and, as a consequence, one cannot accurately model variance in SES using the data at hand (job status and education). Only the model presented in Fig. 1b is empirically testable.

In Fig. 1b, the two measured indicators, job status and education, completely define a composite variable, $\eta2$. Thus, $\eta2$ contains information on the variance of job status and education, but contains no information on the variance of income. Accordingly, $\eta2$ is not the same thing as SES, and information on $\eta2$ does not necessarily provide information on SES. Under the logic of the formative model, $\eta2$ is error free, and so in Fig. 1b, the error term ($\zeta2$) has a magnitude of zero. Drawing on the arguments in *IFV*, the authors suggest that, in cases where formative measures are used in empirical studies, one cannot draw conclusions about how SES relates to anything, since one does not know the variance of SES (information on income is missing): one can only draw conclusions about how $\eta2$ is related to other variables.

What happens if one follows Rigdon's advice and adds some endogenous variables to the model? Will this provide information about the variance of the formative latent SES construct (i.e., $\eta1$)? In order to know about the variance of SES, information on x1 and x2 is needed (and is available in the fictitious data set), and on $\zeta1$, which is missing from the fictional data set. Rigdon's suggested addition of endogenous variables to the model initially seems to offer some assistance on this front. For example, Fig. 1c uses fertility (y1) and life expectancy (y2) as potential endogenous variables of latent variable $\eta3$ (SES is believed to be associated with health-related outcomes such as these: Bollen, Glanville, & Stecklov, 2007; Burström, Johannesson, & Diderichsen, 2005). Adding such variables identifies the model, and provides an error estimate, $\zeta3$. Accordingly, it appears that the addition of the endogenous variables in Fig. 1c provides information on the variance of the formative latent SES construct, since the researcher has information on x1, x2 and $\zeta3$.

However, it would be a mistake to assume that the estimate of $\zeta3$ provides any information on $\zeta1$, or any information on $\zeta1$'s relationship with SES ($\eta1$). Instead, on adding the endogenous outcomes, $\eta3$'s meaning changes from that of $\eta1$. That is, $\eta3$ now is not a variable whose meaning is grounded in the xs and a ζ term: with the addition of the endogenous variables, $\eta3$ becomes a latent variable that has its meaning and variance grounded in the covariance of (i.e. the common factor underpinning) fertility and life expectancy (Howell, Breivik, & Wilcox, 2007).

The point being made becomes obvious when one considers that, in Fig. 1c, the conceptual content of $\eta1$ has no impact on the value of $\zeta3$ that is returned upon statistical analysis. The following example demonstrates this point. Imagine that a researcher decides to change the conceptual definition of SES, so that it contains a fourth component, access to non-financial resources. However, the researcher does not collect new data and so only has information on job status and education: income and access to financial resources are unmeasured in the fictional dataset. Under this scenario, and in order to accommodate the change in the conceptual meaning of SES in Fig. 1a, the value of $\zeta1$ changes to include both income and access to non-financial resources. Yet, when one ripples this change in the definition of SES, and the consequent change in the value of $\zeta1$, through to Fig. 1c, the numerical solution produced by running Fig. 1c on the fictional data remains constant, regardless of whether SES's definition contains or excludes access to financial resources: none of the model estimates (including that for $\zeta3$) change. This is because the value of $\zeta3$ is not dependent on the meaning of SES, and because $\zeta3$ does not provide information on $\zeta1$. In fact, $\zeta3$ merely represents the unexplained variance that would be observed as a result of using x1 and x2 to predict the common factor underpinning y1 and y2. The upshot is that, while the addition of endogenous variables to Fig. 1a may produce a new model that is statistically identifiable, the new model (Fig. 1c) is not a model that can claim to measure SES.

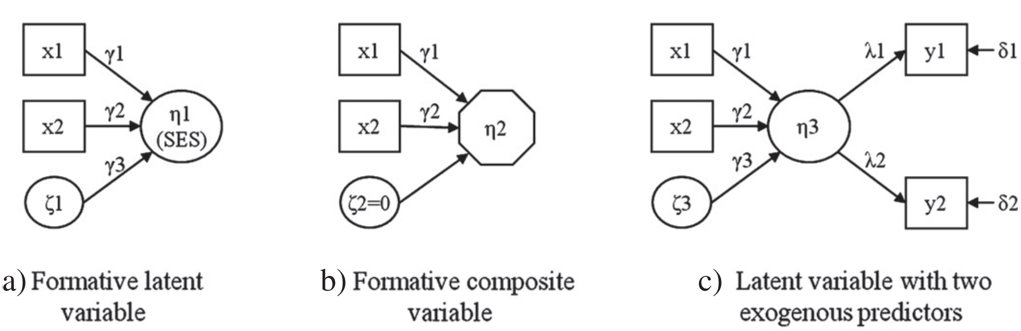

Fig. 1. Formative models and error term identification.