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Proportional structural effects of formative indicators

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Abstract

Formative constructs must influence two or more distinct outcome variables for meaningful tests of the formative conceptualization. Because the construct mediates the effects of its indicators, the indicators must have effects on the outcomes that are proportional to their effects on the formative construct itself. This constraint has important implications for developing and testing formative models. This study demonstrates the existence of the constraint, shows that researchers must consider proportionality as a criterion for evaluating the formative conceptualization, provides examples of indicators having different effects and interpretations depending on the outcome variables used, discusses the selection of outcomes to provide rigorous rather than trivial tests of the formative conceptualization, and contends that the formative nature of constructs cannot be justified in isolation from the consideration of outcome variables. In addition, the study demonstrates the importance of considering how the scaling of the formative construct influences the significance of the effects in the model.

Keywords: Formative constructs; Causal indicators; Measurement; Likelihood ratio tests

1. Introduction

The literature on formative indicators suggests various criteria for determining whether a construct should be treated as reflective or formative (e.g., Bollen and Lennox, 1991; Cohen et al., 1990; Diamantopoulos and Winklhofer, 2001; Edwards and Bagozzi, 2000; Jarvis et al., 2003; Petter et al., 2007). Some criteria deal with constructs and indicators in isolation from other constructs. For example, reflective indicators of a unidimensional construct manifest the same underlying concept. Changes in the construct lead to changes in the indicators, so that they should be internally consistent and conceptually interchangeable. Adding or removing indicators may affect reliability but does not change the nature of the construct. Certain tetrads–functions of the covariances between four or more variables–should equal zero within sampling error (Bollen and Ting, 2000). Conversely, formative indicators define the construct. A change in a formative indicator leads to changes in the construct, without necessarily affecting any of the construct's other indicators. Formative indicators may therefore be conceptually distinct and internally inconsistent, with no expectations for tetrads to equal zero. Researchers should include a census of indicators in their models, because "omitting an indicator is omitting a part of the construct" (Bollen and Lennox, 1991, p. 308).

Other distinctions between reflective and formative models involve relationships of constructs or indicators with other constructs. Formative constructs require such relationships, because "without external criteria, a cause induced latent trait [formative construct] is psychologically uninterpretable" (Bollen and Lennox, 1991, p. 312). Jarvis et al. (2003; MacKenzie et al., 2005) note that reflective indicators should have consistent relationships with other variables in the nomological net, whereas formative indicators may have different antecedents and consequences. In practice, though, researchers normally test formative indicators as exogenous variables, with

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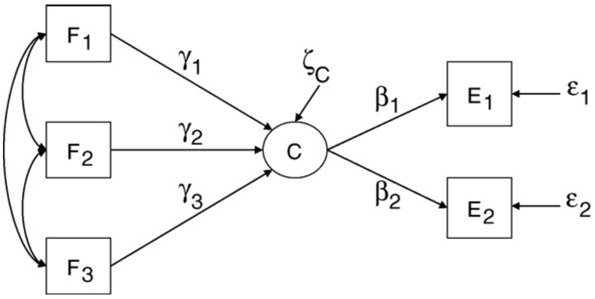

Fig. 1. Example of a formative (MIMIC) model.

their effects on other variables channeled solely through the formative construct. For both reflective and formative constructs to have an identified error term, they must have direct effects on at least two distinct measured variables or reflective constructs (e.g., Bollen and Davis, 1994; MacCallum and Browne, 1993). Unlike reflective constructs, formative constructs mediate the effects of their indicators on other variables, constraining their indicators to have the same proportional influence on the outcome variables (e.g., Blalock, 1969; Bollen and Davis, 1994; Hayduk, 1987).

This study shows that the proportional effects implied by formative constructs have important implications for structural equation modeling. The next section demonstrates the proportionality constraint analytically and empirically, to show that rejection of the constraint implies rejection of the formative conceptualization. The first empirical example (Section 2.2) illustrates the important effects that the scaling of the formative construct may have on statistical inferences. Another set of examples (Section 3.1) shows that acceptance of the constraint with one group of outcome variables does not imply acceptance with other groups of outcome variables. These examples also provide a foundation for discussing problems with the use of reflective indicators of a single construct in testing formative models. Finally, Section 4.2 illustrates the effects that the selection of outcome variables may have on the interpretation of the formative construct.

2. Proportional effects of formative indicators

2.1. Analytical demonstration

Fig. 1 depicts a simple model with three indicators (F_i) and two effects (E_j) of the formative construct (C). (Such models are often called MIMIC models, for multiple indicators-multiple causes). Following Blalock (1969, p. 43), a model with m causal indicators and h effects represents formative construct C as

$$C = \gamma_1 F_1 + \gamma_2 F_2 + \ldots + \gamma_m F_m + \zeta_C, \tag{1}$$

where ζ_C symbolizes the influence of all unmeasured determinants of C. If

$$E_j = \beta_j C + \varepsilon_j, j = 1, 2, \ldots, h, \tag{2}$$

where ε_j symbolizes the influence of all unmeasured determinants of E_j, then substitution of Eq. (1) into Eq. (2) yields

$$E_j = \beta_j(\gamma_1 F_1 + \gamma_2 F_2 + \ldots + \gamma_m F_m) + (\beta_j \zeta_C + \varepsilon_j). \tag{3}$$

This equation denotes the effect of F_i on C as γ_i, and the effect of C on E_j as β_j. C mediates the effect of F_i on E_j, which is simply the product $\gamma_i\beta_j$. The relative effect of F_i on two outcomes E_j and E_k is $\gamma_i\beta_j/\gamma_i\beta_k$ or β_j/β_k. Consequently, the formative indicators have proportional effects on the variables the formative construct influences. Evidence that an indicator's effects violate the proportionality constraint would cast doubt on the indicator's relevance to the formative construct. For example, if C has twice the effect on E_j as on E_k, then every indicator F_i should also have twice the effect on E_j as on E_k, within sampling error. In this model, a variable F_i with an effect on E_j that is significantly more or less than twice the indicator's effect on E_k fails to function as an acceptable formative indicator.

2.2. Empirical illustration

2.2.1. Alternative scalings of the formative construct

Maignan et al. (1999, p. 457) "define corporate citizenship as the extent to which businesses meet the economic, legal, economic, and discretionary [philanthropic] responsibilities placed on them by their various stakeholders." In two studies, they show that measures of the four citizenship dimensions function as reflective indicators of overall corporate citizenship. However, the dimensions arguably satisfy criteria for classification as formative indicators, such as the possibility that changes in each dimension may take place independently of the other three (e.g., Jarvis et al., 2003). Data from Maignan et al.'s (1999) Study 1 allow a test of this possibility. Analysis of all four dimensions indicates that at most three of them function as significant formative indicators of corporate citizenship. For illustrative purposes, legal, economic, and discretionary citizenship constitute the formative indicators, and customer loyalty, business performance, and employee commitment are the outcome variables (see Fig. 2).

In both formative and reflective models, latent variables are unobservable and have no scale of their own, and therefore require a unit of measurement for parameter estimates to be statistically identified and estimated (e.g., Bollen, 1989). Researchers can set the scale of an observed variable as the

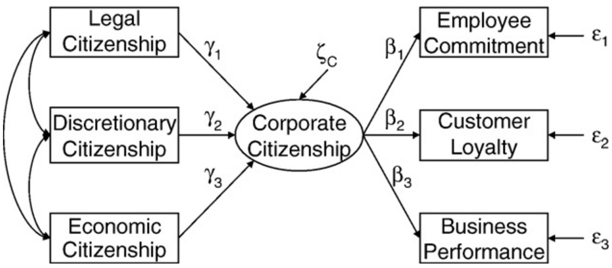

Fig. 2. Model of scalings 1 through 5 in Table 1.

unit of measurement by fixing to 1.0 a path from a formative indicator to the formative construct, or from the formative construct to an outcome variable. Another possible scaling fixes the variance of the formative construct to 1.0. Unfortunately, the method used to set the scale may affect tests of significance of model parameters. Gonzalez and Griffin (2001, pp. 261–262) show that "the reason [significance tests] vary across different model identifications is because the standard errors are typically computed using an approximation that is influenced by how the model is identified." To illustrate the relevance of scaling considerations in formative models, Table 1 presents the results of five different formative analyses using Maignan et al.'s data. In all of the analyses, the error variance of the formative construct (ζ_C in Eq. (1)) is a free parameter. Various paths equal 1.0 in the first four examples: from two citizenship dimensions to the formative construct, and from the formative construct to two outcome variables. The fifth scaling standardizes the formative construct to a variance of 1.0. For ease of interpretation, this analysis also standardizes the structural coefficients.

LISREL 8.80 (Jöreskog and Sörbom, 1996) with maximum likelihood estimation generates the empirical findings. Table 1 shows that all five models fit the data exactly the same (chi-square = 15.62 with 6 *d.f.*; CFI = .98). The estimates illustrate the proportional effects imposed by the formative model on each indicator, controlling for the other indicators. For example, Scaling 3 in Table 1 estimates that corporate citizenship has 2.16 times as much effect on business performance as on customer loyalty, and 2.76 times as much effect on employee commitment. Each indicator of corporate citizenship therefore has 2.16 times as much effect on performance as on loyalty, and 2.76 times as much on commitment. To illustrate, using four decimal places to reduce rounding error, the standardized values in Scaling 5 show that legal citizenship has an effect on performance of $.2446 \times .5820 = .1424$, which is 2.16 times its effect on loyalty of $.2446 \times .2699 = .0660$.

The alternative scalings show that the specification of the formative construct's unit of measurement can influence substantive conclusions. The degree of significance varies for some relationships depending on the scaling of the formative construct. Both Scalings 4 and 5 indicate that all estimated effects are significant at $p < .01$. Scalings 1, 2 and 3 indicate that several paths are significant at only $p < .05$. Therefore, in this example, alternative scaling methods lead to somewhat different conclusions.

2.2.2. Likelihood ratio tests

Because likelihood ratio tests do not vary with different methods of setting the scale of the latent variable, Gonzalez and Griffin (2001) recommend them as an alternative to the Wald test typically implemented in programs for structural equation modeling. The likelihood ratio test requires fixing each free parameter of interest to the value implied by the null hypothesis, then comparing the chi-square value of the resulting model to the chi-square value of the original model. Comparing the square root of the difference to the normal distribution provides a test of significance. For example, setting the path from legal citizenship to the formative construct equal to zero yields a chi-square value of 26.28 with 7 degrees of freedom. The increase from the original model is 26.28–15.62 = 10.66, with a square root of 3.27. This and the other likelihood ratio test results appear in Table 1 following Scaling 5.

Table 1
Alternative models for indicators and outcomes of corporate citizenship

Source	Scaling 1		Scaling 2		Scaling 3		Scaling 4		Scaling 5		Likelihood-ratio test	Revised model	
→Effect	Estimate	*t*	Estimate	*t*	Estimate	*t*	Estimate	*t*	Estimate	*t*		Estimate	*t*
Legal citizenship													
→*Corporate citizenship*	1	–	.95	2.10*	.07	2.50*	.18	3.29**	.24	3.35**	3.27**	.25	2.56*
Discretionary citizenship													
→*Corporate citizenship*	1.05	2.10*	1	–	.07	2.58**	.19	3.49**	.26	3.56**	3.34**	.36	3.14**
Economic citizenship													
→*Corporate citizenship*	2.31	2.73**	2.20	2.89**	.15	3.40**	.42	7.39**	.57	8.11**	6.91**		
→Customer loyalty												.16	2.17*
→Business performance												.49	7.36**
→Employee commitment												.34	5.37**
Corporate citizenship													
→Customer loyalty	.07	2.50*	.07	2.58**	1	–	.36	3.59**	.27	3.67**	3.63**	.16	1.79
→Business performance	.14	3.17**	.15	3.36**	2.16	3.46**	.78	7.74**	.58	8.64**	8.13**	.17	2.10*
→Employee commitment	.18	3.29**	.19	3.49**	2.76	3.59**	1	–	.74	11.38**	10.79**	.79	3.87**
SMC for *Corporate citizenship*	.79		.79		.79		.79		.79			.28	
Chi-square	15.62*		15.62*		15.62*		15.62*		15.62*			3.36	
d.f.	6		6		6		6		6			4	
CFI	.98		.98		.98		.98		.98			1.00	
RMSEA	.09		.09		.09		.09		.09			.00	
SRMR	.04		.04		.04		.04		.04			.02	

The data are from Maignan et al. (1999). The formative construct (corporate citizenship) is shown in italics. Scaling 5 and the revised model standardize the formative construct and all effect estimates. Standardized parameter estimates for Scalings 1–4 equal the values shown for Scaling 5.
*$p < .05$ **$p < .01$.

The likelihood ratio test is cumbersome, and potentially misleading under some circumstances (Stoel et al., 2006). The results in Table 1 suggest that standardizing the latent variable (Scaling 5) produces t values similar to or even larger than those provided by the likelihood ratio test. In comparing both methods for all of the other analyses reported in this paper, the two tests correlate almost perfectly (r=.997), with a small average difference of .14 in favor of the Wald test. Given the consistency of the two versions, the slightly greater power of the Wald test, and the simplicity of interpreting the standardized effect estimates, this paper shows only the standardized scalings for subsequent analyses.

2.2.3. Revised model of the effects of discretionary citizenship

The initial results in Table 1 suggest that legal, economic, and discretionary citizenship function as formative indicators of corporate citizenship when the outcome variables consist of customer loyalty, business performance, and employee commitment. However, LISREL diagnostics indicate that this conclusion is premature. In particular, LISREL provides modification indices (Sörbom, 1989) that estimate the change in model fit resulting from freeing a constrained parameter. Modification indices are distributed as chi-square variables with one degree of freedom. In the Maignan et al. example, four modification indices of 6.99 or greater suggest that adding paths from economic or discretionary citizenship to employee commitment or business performance would significantly improve model fit. Consequently, economic or discretionary citizenship, or both, apparently fail to have the same proportional influence as legal citizenship on employee commitment.

As shown in the final analysis in Table 1 and depicted in Fig. 3, when economic citizenship influences the outcomes directly rather than through the formative corporate-citizenship construct, the model fits very well (chi-square=3.36 with 4 *d.f.*; CFI=1.00). In this model, legal and discretionary citizenship have the same proportional effects on the outcome variables, but economic citizenship does not; in fact, economic citizenship has no significant effect on one of the three outcomes. These results indicate that significant t-values and acceptable model fit can give a misleading picture of whether individual variables function as effective formative indicators.

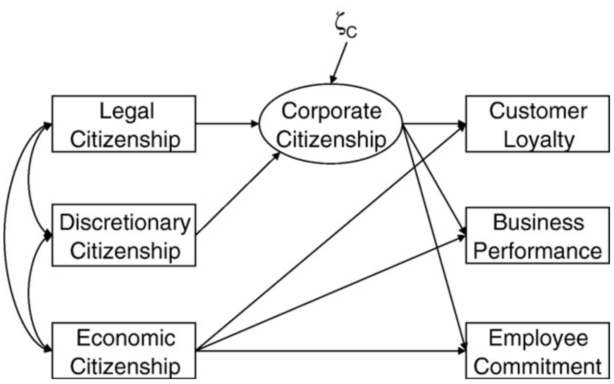

Fig. 3. Revised model in Table 1.

3. Outcome-specific formative constructs

3.1. Overview and illustration

The analyses of Maignan et al.'s data illustrate the potential inaccuracy of classifying indicators as formative or reflective in isolation, without considering which specific other variables a formative construct may influence. Eq. (3) implies that the estimated effects of the formative construct may vary across outcome variables, and therefore the fit of the proportionality constraint on coefficients β_j and β_k depends on the choice of effects E_j and E_k. As Heise (1972, p. 160) notes, "The form of a latent variable always is dependent on the problem in which it appears… Thus the meaning of the latent construct is as much a function of the dependent variable[s] as it is a function of its indicators…". For example, the amount of beer, wine, and distilled spirits consumed may serve as formative indicators of alcohol consumption when the outcome variables examined reflect symptoms of intoxication (e.g., Bagozzi, 1994; Chin, 1998). But if the outcome variables reflect satiety, then beer, wine, and spirits consumption could serve as indicators of calorie or liquid intake.

Hennig-Thurau et al. (2006) present data on characteristics of 331 movies used to test a broad model of movie success in theaters and on video. Their model includes the effects of a variety of movie characteristics, post-filming studio activities, and external factors, on multiple measures of financial performance. For illustrative purposes, this section presents analyses of the effects of personnel attractiveness on several different sets of outcome variables. Consistent with Hennig-Thurau et al. (2006), measures of star power, director power, and producer power serve as formative indicators of personnel attractiveness. Table 2 shows the results of the analyses, with all variables standardized and maximum likelihood estimates obtained using LISREL 8.80.

Personnel attractiveness (construed as the resources of the movie's investors) could influence the *distribution* of a new movie, influencing the number of theater screens showing a movie during its first and second weeks of availability. Labeling these variables Screens 1 and Screens 2, respectively, the first analysis in Table 2 shows that the formative model fits the data (chi-square=3.72, *d.f.*=2; CFI=.99). Star power has an effect two-thirds greater than director power, with standardized coefficients of .20 and .12, respectively. The .10 effect of producer power is not significant at the .05 level.

Personnel attractiveness (construed as popularity, reputation, or movie quality) could also influence various short-term and long-term *viewer evaluations* of a movie. With two measures of evaluations, Metascores of professional reviews from Metacritic.com and viewer ratings from the Internet Movie Database (IMDB.com), the formative model fits the data quite well (chi-square=.86, *d.f.*=2; CFI=1.00). However, only director power has a significant effect on the formative construct at the .05 level. With short-term and long-term *box office* as the outcome measures, the model again fits the data (chi-square=3.68, *d.f.*=2; CFI=.99) and all three power measures have significant effects ($t \geq 2.49$). Star power, director power, and producer

Table 2
Formative constructs with alternative outcome variables

Source	Distribution		Viewer evaluations		Box office		Rentals		Rentals revised	
→Effect	Effect	*t*	Effect	*t*	Effect	t	Effect	*t*	Effect	*t*
Star power										
→*Personnel attractiveness*	.20	3.71**	−.05	−.91	.14	2.49*	−.01	−.23		
→VHS rentals									−.03	−.57
→DVD rentals									.12	2.18*
Director power										
→*Personnel attractiveness*	.12	2.20*	.11	1.96*	.20	3.60**	.15	2.61**	.15	2.68**
Producer power										
→*Personnel attractiveness*	.10	1.85	−.04	−.67	.15	2.74**	.31	5.14**	.31	5.27**
Personnel attractiveness										
→Screens 1	.99	19.72**								
→Screens 2	.97	19.43**								
→Metascores			1.00	6.59**						
→IMDB			.83	6.40**						
→Short-term box office				.87	12.55**					
→Long-term box office				.95	13.28**					
→VHS							.93	8.51**	.91	8.83**
→DVD							.60	7.33**	.62	7.70**
SMC for *Personnel attractiveness*	.06		.02		.08		.11		.11	
Chi-square	3.72		.86		3.68		11.42**		2.46	
d.f.	2		2		2		2		1	
CFI	.99		1.00		.99		.94		.99	
RMSEA	.05		.00		.05		.12		.07	
SRMR	.01		.01		.01		.04		.02	

The data are from Hennig-Thurau et al. (2006). The formative construct (personnel attractiveness) is shown in italics. Effects are standardized values.
*$p<.05$ **$p<.01$.

power have significant effects on the formative construct of .14, .20, and .15, respectively. With VHS and DVD *rentals* as outcome measures, the model does not fit the data (chi-square = 11.42, *d.f.* = 2; CFI = .94). Modification indices suggest that the problem is a violation of the proportionality constraint: Star power has a lower effect on VHS rentals than on DVD rentals (modification index = 7.96 for both). With star power allowed to have differential effects on the rental measures, the model fits the data (chi-square = 2.46, *d.f.* = 1; CFI = .99), and director and producer power have proportional effects on the VHS and DVD rentals. Star power has a positive, significant influence on DVD rentals, with a nonsignificant effect on VHS rentals.

Analysis with all eight outcome measures produces a very poor fit to the data (chi-square = 1351.5, *d.f.* = 41; CFI = .51). Treating each pair of related outcomes as reflective measures of a latent variable improves the fit, but not to acceptable levels (chi-square = 326.1, *d.f.* = 37; CFI = .89). Together, these and the analyses reported in Table 2 demonstrate that the choice of outcome variables may determine the fit, significance, and magnitude of the effects of hypothesized formative indicators.

3.2. Reflective indicators as outcome variables

An occasion that maximizes the opportunity for formative indicators to have proportional effects is when the outcome variables are alternative measures of the same construct—that is, a unidimensional set of reflective measures. As mentioned earlier, a distinction between formative and reflective measures is that reflective measures should have consistent relationships with other variables in the nomological net. Therefore, any set of predictors should have relatively proportional effects on the indicators of a reflective construct. In such cases, the implied proportionality constraints actually provide no test of the formative conceptualization itself.

The above analyses of the movie data illustrate this pattern. In the three models that fit the data, the correlations and conceptual relationships between the pairs of outcome variables are strong ($r \geq .83$), suggesting that each pair provides alternative measures of a single construct. Though VHS and DVD rentals have a substantial correlation ($r = .56$), they nevertheless do not show the same pattern of correlations with other variables. Accordingly, the proportionality constraint fails in the model with VHS and DVD rentals as outcome variables.

Table 2 also illustrates a pattern that Howell et al. (2007, p. 242) discuss: when outcome variables "correlate strongly, there is more covariation … to be explained, and thus more error variance, and vice versa." Consequently, formative indicators may tend to explain less variance as the correlations between outcome variables increase. In Table 2, where the outcome variables are highly-correlated, the variance explained by the formative indicators is .11 or below. Conversely, the average correlation between outcome variables in Table 1 is just .26, and the variance explained is substantially higher than in Table 2.

4. Proportional structural effects and omitted formative indicators

4.1. Overview

As noted previously, because the meaning of a formative construct depends on the indicators used, researchers should try to assess the construct's entire content domain (e.g., Bollen and Lennox, 1991; Diamantopoulos and Winklhofer, 2001; Williams et al., 2003). Moreover, a given set of indicators may refer to more than one construct, depending on the theoretical framework and outcome variables considered. Therefore, the domain of a construct and the range of appropriate indicators may vary from study to study.

In empirical tests of formative models, evidence for or against a given indicator often depends on the other indicators and the outcome variables used: "The latent variable, as defined by the parameters of the model, is not just a composite formed from its indicators; it is the composite that best predicts the dependent variable[s] in the analysis when the other independent variables in the analysis are controlled" (Heise, 1972, p. 160). Adding or omitting indicators or outcomes may change the other indicators' effects on the outcomes, making an acceptable indicator become unacceptable or vice versa. Therefore, alternative combinations of a formative construct's indicators may provide inconsistent results for a given set of outcomes.

4.2. Illustrating the effects of adding indicators and outcomes

Law and Wong (1999) contrast formative and reflective models using five measures of job perceptions, two other exogenous variables, and two outcome variables. Using their data from 204 business-school graduates for illustrative purposes, with maximum likelihood estimates given by LISREL 8.80, Tables 3 and 4 report results for several alternative models with job perceptions as the formative construct. Table 3 uses two outcome variables: job satisfaction and employees' liking of their supervisor. The alternative models use different formative indicators of job perceptions, representing five core job characteristics from the Job Diagnostic Survey (Hackman and Oldham, 1975): feedback, task significance, skill variety, task identity, and autonomy. In all the results shown, the model fits the data with no substantial modification indices, consistent with the proportionality constraint. According to the *t*-values from the standardized solution, the first model indicates that feedback and task significance have significant effects on the outcome variables. Skill variety is significant when added to the model, but the effects of task significance become nonsignificant. Omitting task significance and adding task identity produces another satisfactory model, with all three indicators having significant influences on the job perception construct. However, adding autonomy to the model makes the effects of task identity become nonsignificant. Returning task significance to the model to assess all five available indicators of job perceptions shows that both task significance and identity continue to have nonsignificant effects.

Table 4 is similar to Table 3 except for the addition of turnover intentions to the set of outcome variables. The results for the first three models in Table 4 match those in Table 3: task significance has significant effects when paired with feedback; the effects of task significance become nonsignificant with the addition of skill variety as an outcome variable; and task identity has significant effects when the model includes task identity and omits task significance. Also as before, the effects of autonomy are significant and the effects of task identity become nonsignificant after adding autonomy to the model.

Table 3
Effects of alternative indicator selection with two outcome variables

Source	Indicator Set 1		Indicator Set 2		Indicator Set 3		Indicator Set 4		Indicator Set 5	
→Effect	Effect	*t*	Effect	*t*	Effect	*t*	Effect	*t*	Effect	*t*
Feedback										
→*Job perceptions*	.43	4.75**	.29	3.32**	.24	2.92**	.20	2.55*	.20	2.56*
Task significance										
→*Job perceptions*	.18	2.08*	.06	.65					−.02	−.33
Skill variety										
→*Job perceptions*			.40	4.37**	.29	3.26**	.24	2.90**	.25	2.87**
Task identity										
→*Job perceptions*					.20	2.33*	.00	.01	.00	.01
Autonomy										
→*Job perceptions*							.38	4.18**	.38	4.16**
Job perceptions										
→Job satisfaction	.80	6.27**	.79	7.38**	.87	7.17**	.88	7.96**	.89	7.91**
→Liking	.41	4.63**	.42	5.07**	.38	4.63**	.38	4.75**	.37	4.71**
SMC for *Job perceptions*	.28		.40		.36		.43		.43	
Chi-square	3.08		3.10		4.50		4.54		7.61	
d.f.	1		2		2		3		4	
CFI	.98		1.00		.99		1.00		.99	
RMSEA	.10		.05		.08		.05		.06	
SRMR	.03		.02		.02		.02		.03	

The data are from Law and Wong (1999). The formative construct (job perceptions) is shown in italics. Effects are standardized values.
$*p<.05$ $**p<.01$.

Table 4
Effects of alternative indicator selection with three outcome variables

Source	Indicator Set 1		Indicator Set 2		Indicator Set 3		Indicator Set 4		Indicator Set 5	
→Effect	Effect	*t*	Effect	*t*	Effect	*t*	Effect	*t*	Effect	*t*
Feedback										
→*Job perceptions*	.41	5.92**	.28	3.84**	.24	3.29**	.18	2.67**	.19	2.69**
Task significance										
→*Job perceptions*	.15	2.07*	.04	.58					−.03	−.46
Skill variety										
→*Job perceptions*			.33	4.43**	.26	3.30**	.21	2.80**	.21	2.82**
Task identity										
→*Job perceptions*					.19	2.42*	.02	.18	.01	.17
Autonomy										
→*Job perceptions*							.34	4.42**	.34	4.46**
Job perceptions										
→Job satisfaction	.89	12.25**	.91	13.27**	.94	13.67**	.98	14.80**	.99	14.85**
→Liking	.37	4.96**	.37	5.01**	.36	4.92**	.34	4.82**	.34	4.80**
→Turnover intentions	−.74	−10.32**	−.72	−10.37**	−.71	−10.16**	−.67	−9.84**	−.67	−9.79**
SMC for *Job perceptions*	.24		.30		.31		.35		.35	
Chi-square	4.18		6.67		7.13		12.61		17.40	
d.f.	4		6		6		8		10	
CFI	1.00		1.00		1.00		.99		.99	
RMSEA	.01		.02		.03		.05		.06	
SRMR	.03		.03		.02		.03		.04	

The data are from Law and Wong (1999). The formative construct (job perceptions) is shown in italics. Effects are standardized values.
$^*p<.05$ $^{**}p<.0$.

Unlike the results in Table 3, modification indices as high as 5.33 indicate that autonomy violates the proportionality constraint in this model. Further analysis (not shown) reveals that autonomy does have proportional effects on job satisfaction and liking, consistent with the results in Table 3, but its effect on turnover intentions is not as strong as (less negative than) implied by the formative model. Autonomy's disproportionate effects on turnover intentions remain regardless of the inclusion or omission of task identity and significance as formative indicators. Therefore, autonomy's status as a formative indicator of job perceptions depends on the outcome variables considered.

5. Discussion

The premise underlying this study is that the formative construct should completely mediate the effects of the formative indicators on other variables. This premise conforms to previous discussions and applications of formative models (e.g., Collier and Bienstock, 2006; Diamantopoulos, 1999; MacCallum and Browne, 1993; Winklhofer and Diamantopoulos, 2002). If the formative indicators could have direct as well as mediated effects on the outcome variables, then the proportionality constraint would not necessarily hold and would not be a consideration in conceptualizing or testing formative models. However, in this case, the formative construct no longer captures the effects of the components on other variables, raising questions about the meaning and value of the formative conceptualization. The implied meaning of the effects is also unclear, because direct effects are the influence of one variable on another, holding other predictors constant. The indicator is a component of the construct, so that in the presence of a direct effect from an indicator, the effect of the construct on the outcome variable holds constant a part of the construct itself. This pattern is logically inconsistent. In some cases, allowing an indicator to influence an outcome directly does not create a paradox, but instead is equivalent to a model with the variable influencing all the outcomes directly rather than functioning as a formative indicator. In general, attempting to circumvent the proportional structural effects implied by the formative model eliminates the essential nature of formative constructs.

A key implication of this study is that researchers must consider the implied proportionality constraint in conceptualizing and evaluating formative models. Criteria for distinguishing between formative and reflective models that fail to consider both indicators and outcome variables are incomplete. Theoretical justification for formative constructs requires a rationale for why the construct's indicators should have proportional effects on the construct's outcomes. In some cases the rationale will be obvious, as when beer, wine, and spirits consumption are used as formative indicators of alcohol or calorie intake. In other cases the rationale will be more obscure. Socioeconomic status (SES), for example, is arguably a formative construct formed from education, income, and other factors. However, the components of SES tend to have disproportionate effects on other variables (e.g., Cohen et al., 1990; Hayduk, 1987; Howell et al., 2007). A theoretical rationale and empirical evidence for a disparate set of outcomes would help support the formative conceptualization. For SES, such outcomes may include "social attitudes and values, residential choices, and the characteristics of friends and associates," though whether these variables are outcomes or actual indicators of SES is debatable (Cohen et al., 1990, p. 187).

Different outcomes may have different implications for the scope of the causal construct. As stated by Diamantopoulos

(2006, p. 15), "the selection of the 'external' [outcome] variables necessary for achieving identification is just as crucial in formative measurement models as is the selection of the formative indicators themselves." For example, consumption of different forms of alcohol may appear to represent a straightforward formative construct. However, if the outcomes of interest are short-term, adverse physical effects of alcohol consumption–hangovers–the relevant construct may be consumption of light and dark alcoholic beverages rather than consumption of beer, wine, and spirits (e.g., Albie, 2005). Or if the outcomes involve measures of urine levels of ethyl glucuronide (EtG), a test designed to detect alcohol metabolization, relevant indicators may include various foods, medications, personal-care products, and even hand sanitizers, in addition to forms of beverage alcohol (Helliker, 2006). Therefore, guidelines for the development of formative constructs (e.g., MacKenzie et al., 2005) should make the specification of outcomes an integral part of defining the construct, rather than a distinct step that follows construct definition.

The selection of outcome variables also has important implications for the variance explained by a set of formative indicators. Finding that the variance explained is low, so that the error term (ζ_C in Eq. (1)) is high, suggests that the model may exclude important additional causal variables (e.g., Diamantopoulos, 2006). Error terms will tend to be higher when including highly-correlated outcome variables in the model (Howell et al., 2007), so that the amount of variance explained should be interpreted relative to the outcome variables used. If the variance explained is low relative to the outcome variables used, attempting to identify additional formative indicators may be fruitful. At the other extreme, formative indicators can be treated as accounting for all of the variance in the formative construct. However, in these "cases, where the formative model does not include an error term…, no surplus meaning can be attributed to the formative construct; the latter simply becomes a weighted linear combination of its indicators" (Diamantopoulos, 2006, p. 14).

Specification of outcome variables may even help in determining the formative or reflective nature of a construct. Bollen and Ting (2000, p. 18) note that the same variables may be reflective or formative indicators of different constructs: "Indicators of a child's viewing of violent television programs, playing violent video games, and listening to music with violent themes may be causal [formative] indicators of the latent variable of exposure to media violence, but the same measures could be effect [reflective] indicators of another latent variable of propensity to seek violent entertainment." Media exposure and personality traits may have quite different antecedents and consequences, leading to alternative theoretical questions and nomological nets that distinguish between the formative and reflective conceptualizations.

In a sense, this study presents the proportional structural effects of formative models as a problem for the researcher. They must be justified by theory, and their rationale may vary from one group of outcome variables to another. They may also lead to rejection of variables as acceptable formative indicators, even when their effects are individually significant and the model fits overall. Thus, the implied proportional effects add layers of complexity that have not been generally recognized in discussions of formative models. However, as demonstrated by Bollen and Davis (1994), proportionality constraints may also benefit the researcher in that they allow partial investigation of models that would not otherwise be identified. In any case, while proportionality constraints may complicate or enable researchers' efforts to examine formative models, they are a reality that researchers must recognize.

Finally, although scaling effects are not the focus of the study, Table 1 does serve to show that different substantive inferences may depend on how the researcher sets the scale of a formative construct. Therefore, researchers should consider alternative scaling approaches in testing the statistical significance of formative indicators. The likelihood ratio test suggested by Gonzalez and Griffin (2001) is not sensitive to the scaling approach used, but may be difficult to implement and interpret (Stoel et al., 2006). Standardizing the formative construct and the observed variables, then interpreting the traditional Wald tests reported by most programs for structural equation modeling, appears to be a promising alternative. Monte Carlo simulations could investigate this possibility systematically over a wider range of formative (as well as reflective) models.

6. Conclusion

In recent years a growing body of research has identified formative constructs as an alternative to more traditional reflective conceptualizations (e.g., Bollen and Lennox, 1991; Diamantopoulos and Winklhofer, 2001; Edwards and Bagozzi, 2000; Jarvis et al., 2003; MacKenzie et al., 2005; Petter et al., 2007). The extant literature stresses the inputs to formative constructs–their indicators–rather than their effects. As the present study shows, though, the nature and indicators of a formative construct may vary depending on the outcome variables considered, and vice versa. Studies using formative constructs should therefore justify the selection of formative indicators and outcome variables, and provide both conceptual and empirical support for the implied proportional effects of the indicators on the outcomes.

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