The Effect of Misspecification of Reflective and Formative Constructs in Operations and Manufacturing Management Research

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Abstract: This paper highlights theoretical and mathematical differences between formative and reflective measurement models, in the context of academic SEM oriented research in Operations and Manufacturing Management, an area of significant current interest. It discusses problems associated with measurement model misspecification. It further illustrates, using survey data, the effects of possible misspecification on model fit parameters and path coefficients in a nomological model, using the Partial Least Squares (PLS) approach. It then proposes guidelines for the use of the PLS methodology for analyzing formative measurement models.

Keywords: formative, reflective, measurement models, PLS, structural equation modeling, model misspecification

1. Introduction

Structural Equation Modeling (SEM) ("a technique to specify, estimate, and evaluate models of linear relationships among a set of observed variables in terms of generally smaller number of unobserved variables." - Shah and Goldstein, 2006) is widely used in Operations and Manufacturing Management (OM) research to empirically define and validate constructs, and study causal relationships among them. There are two parts to SEM. First is a "Measurement Model", where one tests the relationship of an unobserved variable - a "latent variable" or a "construct"[1], - with a set of observed variables - "indicators" or "measured variables". The second part consists of a "Structural Model" or a "Path Model" - where causal relationships among latent variables and/or measured variables are tested.

A "Measurement Model" can be one of two kinds – a "Reflective Measurement Model"[2] or a "Formative Measurement Model" (Bollen and Lennox, 1991; Edwards and Bagozzi, 2000). (a detailed discussion follows in Section 2). Wrongly modeling a reflective model as formative, and vice versa, is known as "model misspecification". Reflective models have their foundation in the classical test theory (Bollen and Lennox, 1991) and have well developed testing criteria and have been widely used in Operations Management (OM) research. The use of formative models however, has remained limited, due in part to the unavailability of appropriate modeling software and lack of proper testing guidelines, even though their origin can be traced back to the work of Blalock (1961).

Prior work on theoretical and statistical issues regarding the differences between reflective and formative models increases the relevance of studying formative measurement models. First, many measurement models in the OM literature are formative, by the very nature of the theoretical and domain concepts underlying them. Modeling such variables (wrongly) as reflective models leads to a misspecification error (Bollen and Lennox, 1991; Edwards and Bagozzi, 2000; Diamantopolous and Winklhofer, 2001). Second, a misspecification in the measurement model (that measures a latent variable or a construct) impacts the structural paths coming in or going out of the latent variable, thus leading to erroneous path coefficients (Mackenzie et al., 2001; Jarvis et al., 2005). To this end, there is a need for understanding (1) when the use of formative measurement models is appropriate and (2) how such models should be formulated and tested.

Current literatures in other management disciplines (strategic management, marketing, management information systems, and organization behavior, e.g.) have initiated an interesting and important discourse about when and why constructs in their respective fields should be modeled as formative or

[1] We have used the words "Construct" and "Latent Variable" interchangeably
[2] Hereafter we refer to "Reflective (Formative) Measurement Model" as simply "reflective (formative) model".

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reflective, and theoretical and domain related errors resulting from model misspecification (Bollen and Lennox, 1991; Diamantopolous and Winklhofer, 2001; Jarvis et al., 2003; Mackenzie et al., 2001; Hulland, 1999). However research in OM has not fully dealt with these issues.

In this paper, we provide a basis for understanding how formative models can be appropriately used and modeled, with specific attention to the OM literature. Towards this end we (a) discuss differences between formative and reflective measurement models and provide a brief overview of commonly used terminology (Section 2); (b) discuss the effects of model misspecification from a theoretical perspective (Section 3); (c) illustrate, through primary (survey) data, the effects of measurement model misspecification on a particular structural model (Section 4); (d) review the OM literature to examine alternate model specification possibilities and the possible scale of misspecification (Section 5); (e) discuss the implications for researchers in OM who would use these techniques (Section 6); (f) provide some broad recommendations for future research which uses measurement modeling (Section 7).

2. Definitional aspects

2.1 Constructs and measures

A *Construct* is defined as "a conceptual term used to describe a phenomenon of theoretical interest" (Edwards and Bagozzi, 2000, p. 156-157). The phenomenon described by a construct may or may not be directly observable, in which case the construct is a *Latent Construct*. Constructs are measured with the help of *Indicators* (Diamantopolous and Winklhofer, 2001) or *Items* (Law et al., 1998) or *Measures*[3]. These are defined as "an observed score gathered through self report, interview, observation or some other means", (Edwards and Bagozzi, 2000, p. 156). The construct in turn measures a real phenomenon, but incompletely; the un-explained or left over part is known as the *Measurement Error*. A *Measurement Model* is used to depict the relationship between a construct and its measures; it therefore bridges the observed variables (measures) with the unobserved variable (construct) (Byrne, 2001).

When studying the phenomenon of interest, a Measurement Model is usually part of a larger network/model which consists of dependence relationships among constructs. The constructs represent different variables which are germane to understanding the phenomenon. This larger network is known as a "Path Diagram" or a "Structural Model". There can be two types of constructs in a Structural Model: Exogenous and Endogenous. Exogenous constructs are "independent", that is, they act "only as a predictor or 'cause' for other constructs in the model" (Gefen et al., 2000, p. 68). That is, they cause fluctuations or variations in the values of other constructs in the model. Endogenous constructs are "dependent", that is they are "dependent on other variables in at least one causal relationship" (Gefen et al., 2000, p. 67) in the model. In a given Structural Model, exogenous constructs are identified by one or more arrows (signifying causal relationships) coming out of (*but none going into*) them. Endogenous constructs have *at least one arrow going into them*.

2.2 Reflective and formative constructs

A latent construct can be modeled in two ways – Reflective and Formative. In a Reflective model (Edwards and Bagozzi, 2000; Diamantopoulos and Winklhofer, 2001), the construct is viewed as the cause and the measures or indicators its manifestations. Thus, the construct determines its indicators (Bollen and Lennox, 1991), as shown in Figure 1. Some examples of reflective constructs in the OM literature are Supply Chain Integration (Vickery et al., 2003), aspects of TQM practices (Kaynak, 2003) and Supply Chain Performance (Benton and Maloni, 2005) and Flexible Manufacturing (Zhang et al., 2003).

In a Formative model, as shown in Figure 2, the indicators determine (Bollen and Lennox, 1991) or cause (Edwards and Bagozzi, 2000) the construct. According to MacCallum and Browne (1993, p. 533), "in many cases indicators could be viewed as causing rather than being caused by the latent variable measured by the indicators." Formative constructs are also referred to as *Composite Models* (Law and Wong, 1999) or simply, *Indexes* (Diamantopoulos and Winklhofer, 2001). A commonly formative construct in management is Socio-Economic Status (SES) (Bollen and Lennox, 1991; Law and Wong, 1999). SES describes the socio economic position of a person and its indicators are the

[3] In this paper, we use the terms "Measure", "Indicator" and "Item" interchangeably.

person's education, occupational prestige, income and neighborhood. Other examples of formative constructs are life stress (Bollen and Lennox, 1991), motivating potential (Hackman and Oldham, 1976), job satisfaction (Hartline and Ferrell, 1996; Law et al., 1998) and job performance (Mackenzie et al., 2005).

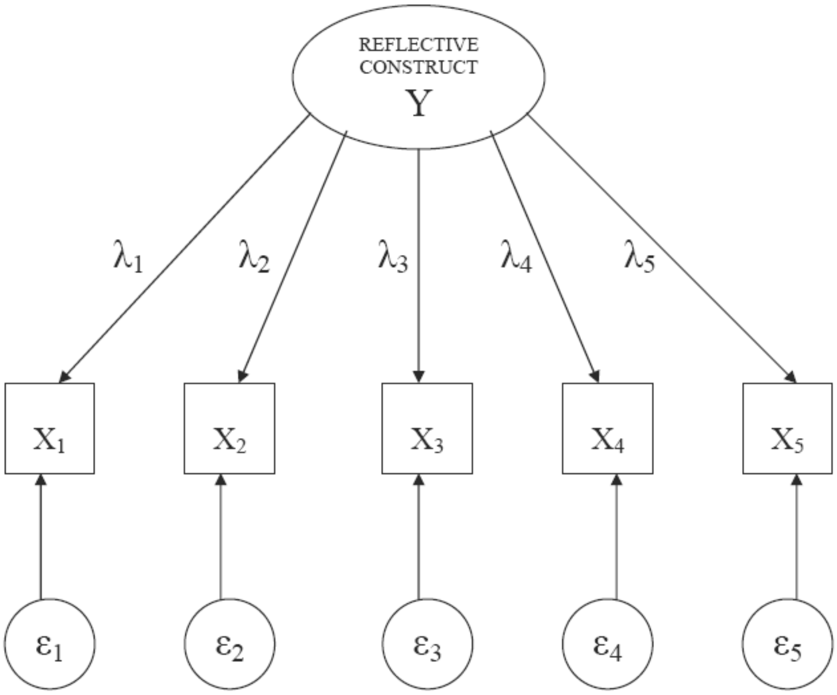


Figure 1: Reflective construct

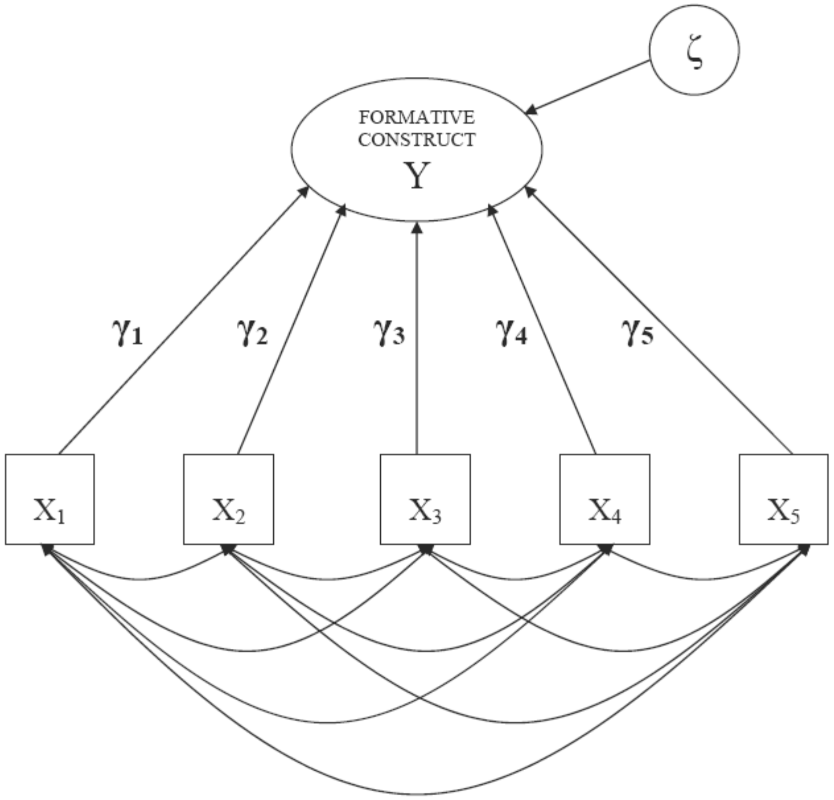


Figure 2: Formative construct

2.3 Differences between formative and reflective constructs

There are five basic differences between reflective and formative constructs which have been described in this section.

2.3.1 Direction of causality between the construct and its indicators

Formative and reflective models have opposing directions of causality vis-à-vis the construct and its measures or indicators. In a reflective construct, the causality flows *from the construct to the indicators*, that is, the indicators are caused by the construct. Thus the indicators are the manifestations of the construct. In a formative construct, the causality flows *from the indicators to the construct*, that is, the indicators cause the construct. Thus, a formative construct is the result of an aggregate of indicator variables.

2.3.2 Notational difference

A reflective construct (Y) is represented as:

$$X_i = \lambda_i Y + \varepsilon_i$$

Where X_i = the i^{th} indicator

Y = the reflective construct

λ_i = coefficient which measures the expected effect of Y on the i^{th} indicator

ε_i = the measurement error for the i^{th} indicator.

Thus, for a reflective construct, each indicator is separately associated with the construct. The covariance of each indicator is shared with all the other indicators, and the random variance for each indicator is treated as error for that indicator (Law and Wong, 1999). Therefore the error terms are reflected separately for each indicator, as unexplained variance for that indicator.

Conversely, a formative construct is represented (Diamantopoulos and Winklhofer, 2001) as:

$$Y = \gamma_1 X_1 + \gamma_2 X_2 + \ldots\ldots\ldots\ldots\ldots\ldots + \gamma_n X_n + \zeta, \text{ or}$$

$$Y = \Sigma \gamma_i X_i + \zeta$$

Where X_i = the i^{th} indicator

Y = the formative construct

γ_i = the weight associated with the i^{th} indicator

ζ = the common error term.

Thus, a formative construct is a summation or an aggregate of its indicators. The only variance, which is treated as error, is the random variance at the construct level (Law and Wong, 1999). Hence the error term is associated with the construct as a whole and not with the individual indicators.

2.3.3 Removal of Indicators

A formative construct is theoretically considered to be the composite of *all* its indicators. Therefore an individual indicator cannot be removed without affecting the definition of the construct. Each indicator of a reflective construct however, being a manifestation of the construct, can be removed if its coefficient is not statistically significant (Bollen and Lennox, 1991).

2.3.4 Correlations between indicators

The indicators in a reflective construct should be highly correlated among themselves since they manifest or represent phenomenon associated with the same construct. Low correlation would indicate poor convergent validity of the construct. Indicators of a formative construct need not be correlated, since they aggregate to form the construct (Bollen and Lennox, 1991).

2.3.5 Identification

A reflective construct can be statistically identified (through a measurement model) in isolation. A formative construct can be statistically identified only by placing it in a larger network (a path model) with other variables (Bollen and Lennox, 1991).

2.4 Unidimensional and multidimensional constructs

A *Unidimensional Construct* (also referred to as *first order* construct) is measured by a single dimension consisting of a set of indicators, as shown in Figure 3. In this context, unidimensionality refers to the existence of a single trait underlying a set of measures (Hattie, 1985). Unidimensional constructs are. A *Multidimensional Construct* is a "higher-level construct that underlies its dimensions" (Law, Wong and Mobley, 1998; p. 743), as shown in Figure 4. The dimensions or facets are distinct, but connected to the higher-level construct through a single theoretical concept. A multidimensional construct does not have a separate existence without its dimensions (Edwards, 2001). The dimensions or facets of a Multidimensional construct can, in turn, be Unidimensional or Multidimensional (Law et al., 1998), leading to constructs of the *second and higher* orders. Most constructs in management research are Multidimensional (Mackenzie et al., 2005).

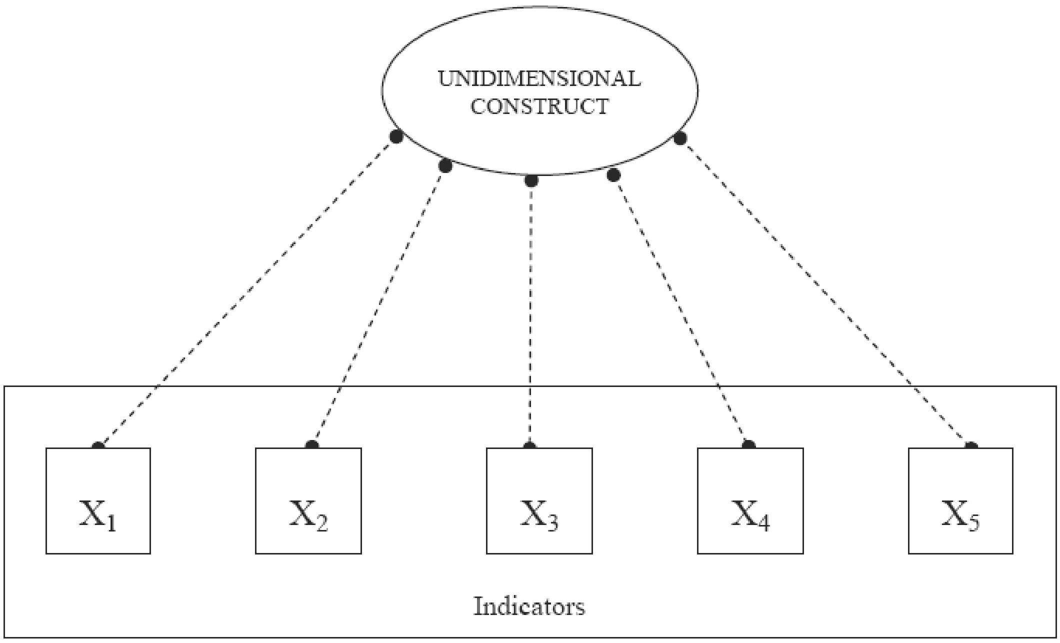


Figure 3: Unidimensional construct[4]

A second order construct can have reflective or formative measurement model/s at its first and second order levels, giving rise to four cases, as shown in Figure 5. Constructs where both orders are reflective (Figure. 5a) have been the most widely studied form of a second order construct in past research. Constructs where both orders are formative (Figure. 5d) or where the first order is formative and the second order is reflective (Figure. 5c) have been rarely studied (Jarvis et al., 2003) in past research. Constructs where the first order is reflective and the second order is formative (Figure. 5d)

[4] The link between the construct and its indicators is a theoretical link and may be formative or reflective depending upon the theory and that will determine the direction of arrows.

are currently being considered by researchers, due in part to the recent availability of appropriate modeling software[5].

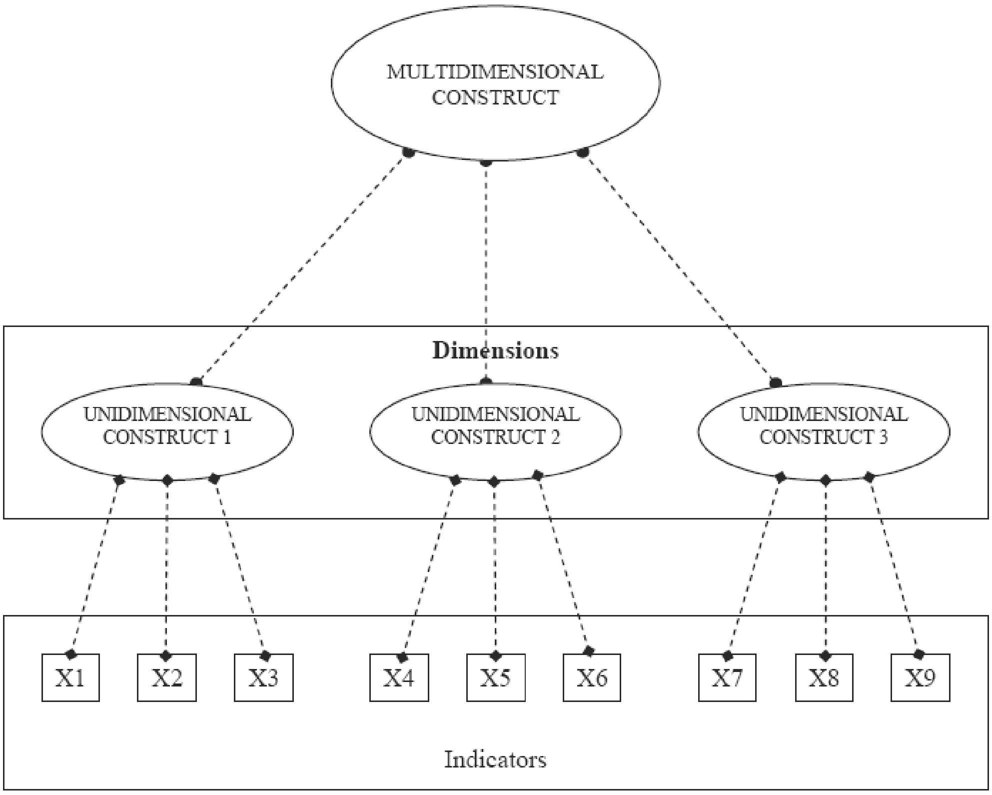
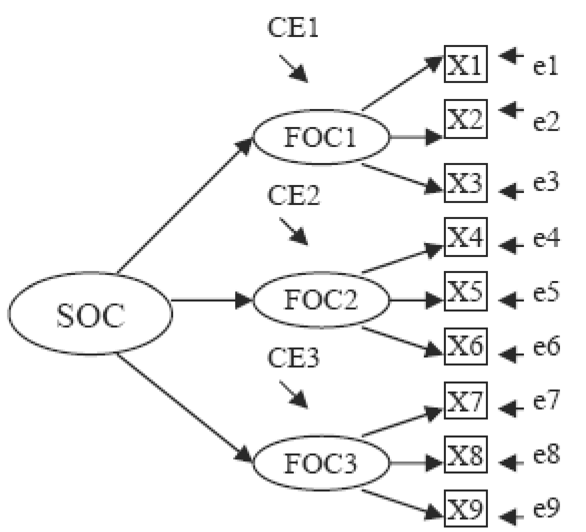
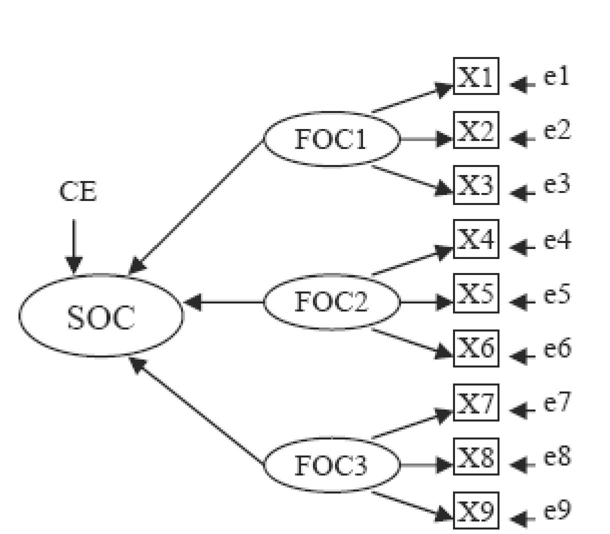


Figure 4: Multidimensional construct[6]

The next section provides an overview of statistical implications of model misspecification.



5a: First Order Reflective,



5b: First Order Reflective, Second Order Formative

[5] There can be other forms of higher order constructs, where the lower orders include both formative and reflective models. These have not been described in detail in this paper due to considerations of complexity.

[6] The link between the multidimensional construct and its dimensions or the dimensions and their indicators are theoretical links and may be formative or reflective depending upon the theory and that will determine the direction of arrows.

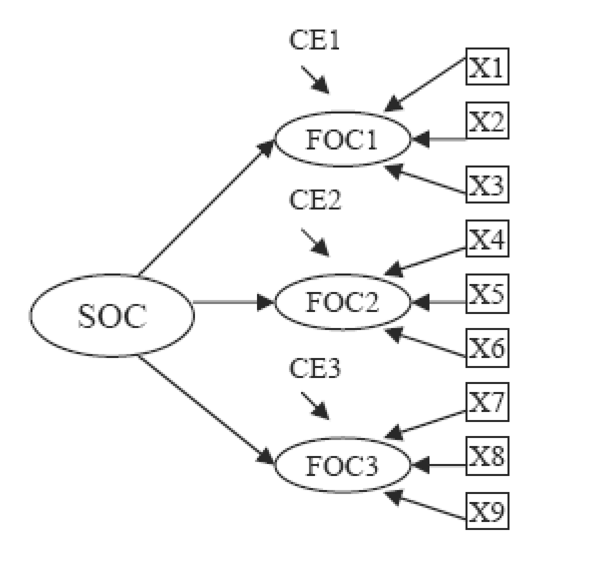
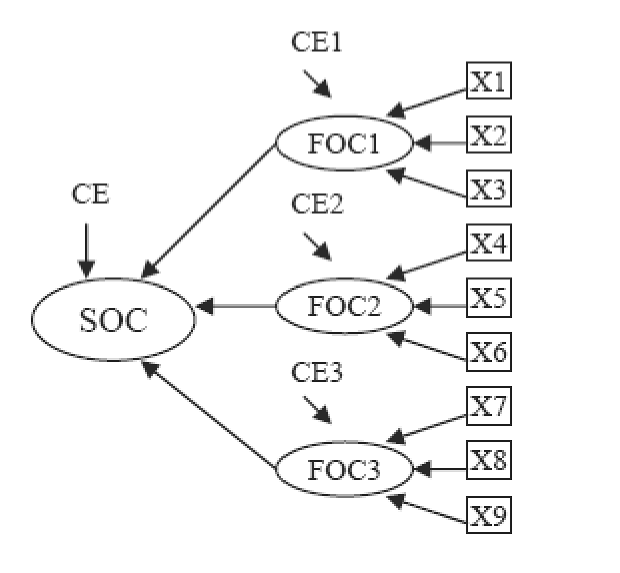
	
5c: First Order Formative, Second Order Reflective	5d: First Order Formative, Second Order Formative

Figure 5: Different forms of first and second order constructs

Note: X's are the Measured Variables, e's are the Error Terms associated with Measured Variables, FOC is First Order Construct, SOC is Second Order Construct, CE's are the Construct Errors.

3. Measurement model misspecification

Model misspecification occurs when a reflective (formative) construct is wrongly modeled as formative (reflective). We explain the effects of measurement model misspecification through a mathematical example involving one exogenous and one endogenous construct in a path model.

The path model is represented by the following equation.

$$Y = \beta X + e$$

Where Y is the endogenous construct

X is the exogenous construct

β is the path coefficient, and

e is the error term.

Given the above equation, the variance of Y, i.e. V(Y) can be written as

$$V(Y) = \beta^2 V(X) + V(e)$$

Where $V(X)$ is the Variance of X, and

$V(e)$ is the Error Variance.

For the sake of simplicity, if we assume that V(e) = 0 then

$$V(Y) = \beta^2 V(X)$$

or $V(Y)/V(X) = \beta^2$

We now assume that the correct measurement model for each construct is formative, and illustrate the effects that occur when one or both are (wrongly) modeled as reflective. Figure 6a represents the correctly specified model.

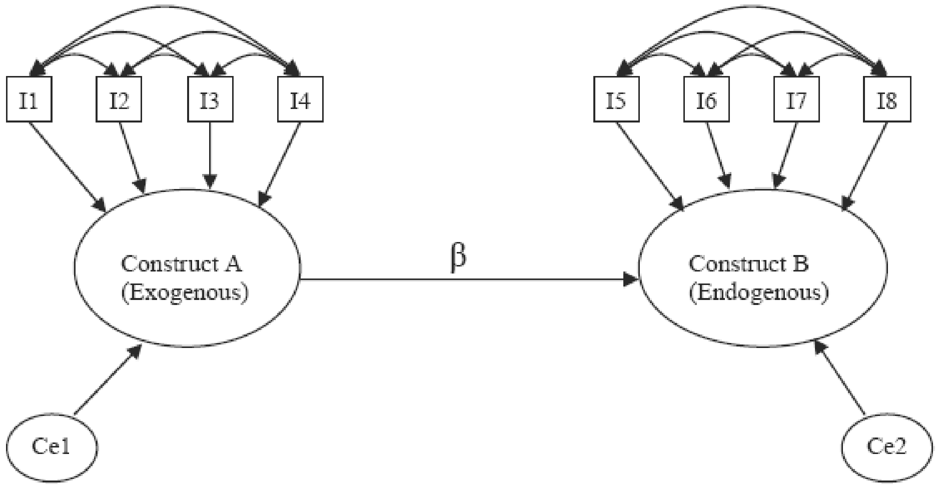


Figure 6a: Correctly specified measurement model (Both A and B are formative constructs)

If the exogenous construct, i.e. X, is misspecified as reflective instead of formative, as shown in Figure 6b, then its variance, i.e. V(X) will decrease, because it will now be shared with the error terms associated with each indicator of X. From the last equation above, the implication that emerges is that for a given V(Y), β^2 will increase, leading to an inflated estimate of the path coefficient. Conversely, if the endogenous construct, i.e. Y, is misspecified as reflective instead of formative, as shown in Figure 6c, then its variance, i.e. V(Y) will decrease because it will now be shared with the error terms associated with each indicator of Y. From the last equation above, for a given V(X), β^2 will decrease, leading to an deflated estimate of the path coefficient. If both constructs are misspecified (Figure 6d), the change in β^2 will depend on the relative magnitudes of change in V(X) and V(Y) respectively. It would also depend on (a) the sample size and (b) the magnitude of inter-item correlations of the constructs (MacKenzie et al. 2005).

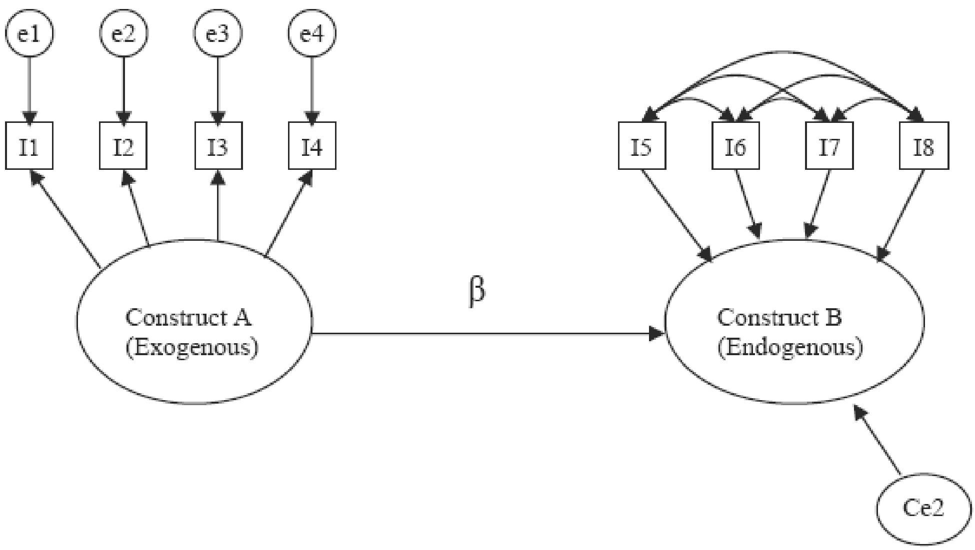


Figure 6b: Incorrectly specified measurement model (Exogenous Construct Misspecified)

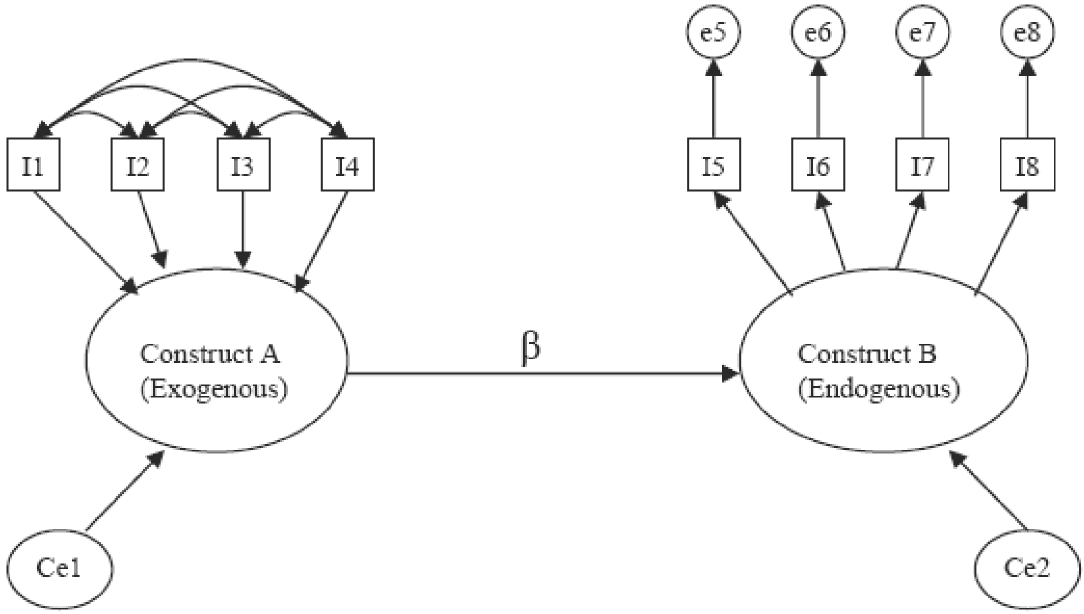


Figure 6c: Incorrectly specified measurement model (Endogenous Construct Misspecified)

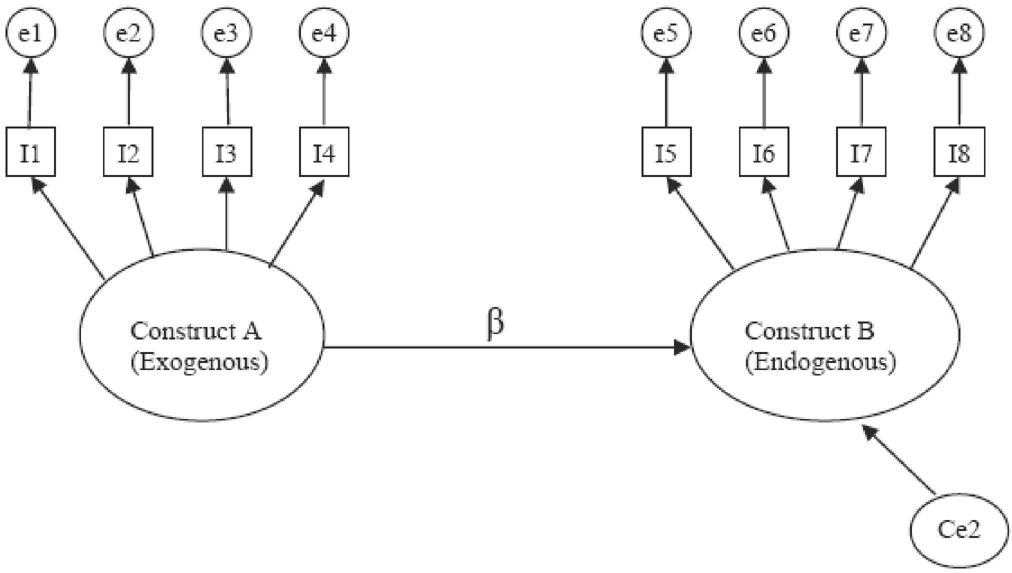


Figure 6d: Incorrectly specified measurement model (Both Constructs Misspecified)

The issue of model misspecification has been addressed to a limited extent in the management literature using mostly Monte Carlo simulations and covariance based SEM (Jarvis et al., 2003; MacKenzie et al., 2005; and Petter et al. 2006). In the next section, we illustrate the possible effects of model misspecification on model parameters and fit statistics using (1) a primary (survey) data set, (2) PLS based SEM, and (3) a prior established nomological path model in the Supply Chain domain.

4. Illustration of model misspecification effects

For illustrating the possible effects of misspecification we use an existing (primary) dataset - Li et al. (2005, 2006) from the domain of Supply Chain Management (SCM). The model that we consider has been excerpted from Li et al. (2005, 2006). It consists of three second order constructs – Supply Chain Management Practices (**scmprac**), Supply Chain Management Performance (**scmperf**), Competitive Advantage (**compadva**) – in a nomological network as shown in Figure 7 and detailed in

Table 3. All first and second order constructs in this network have been previously validated using reflective measurement models by Li et al. (2005, 2006). The endogenous constructs include "**scmperf**" and "**compadva**", while "**scmprac**" is an exogenous construct.

Using Visual PLS 1.04, we tested six different models to analyze and illustrate the effects of alternate specification on model parameters and model fit measures. These models have been shown as cases 1 to 6 in Table 4. For example, in Case 1, all first order constructs were reflective and the three second order constructs were also reflective. Cases 3 and 6 were illustrations of mixed models. In Case 3, all first order constructs were reflective and two of the three second order constructs were formative; In Case 6, all first order constructs were formative and two of the three second order constructs were also formative.

Table 4 shows the results of the structural models in terms of the path coefficients and R square values. The R square value is considered to be a measure of goodness of fit in PLS (Haenlin and Kaplan, 2004). Case 2 displayed the best results. There was not much difference in the values of the path coefficients between Cases 1, 2 and 3. However, the R square value for the **scmperf→ compadva** path was higher for Case 2, compared to Cases 1 and 3. The path coefficients and R square values for Cases 4, 5 and 6 were drastically lower than those for Cases 1, 2 and 3. Compared to Case 2 (which had the highest path coefficient and R square values), the average path coefficient and R square deflations were 38.72% and 91.88% respectively, for cases 4, 5 and 6 in the **scmprac→ scmperf** path. For the **scmperf→ compadva** path**,** the corresponding deflation values were 102.5% and 307.92%, implying poor model fit.

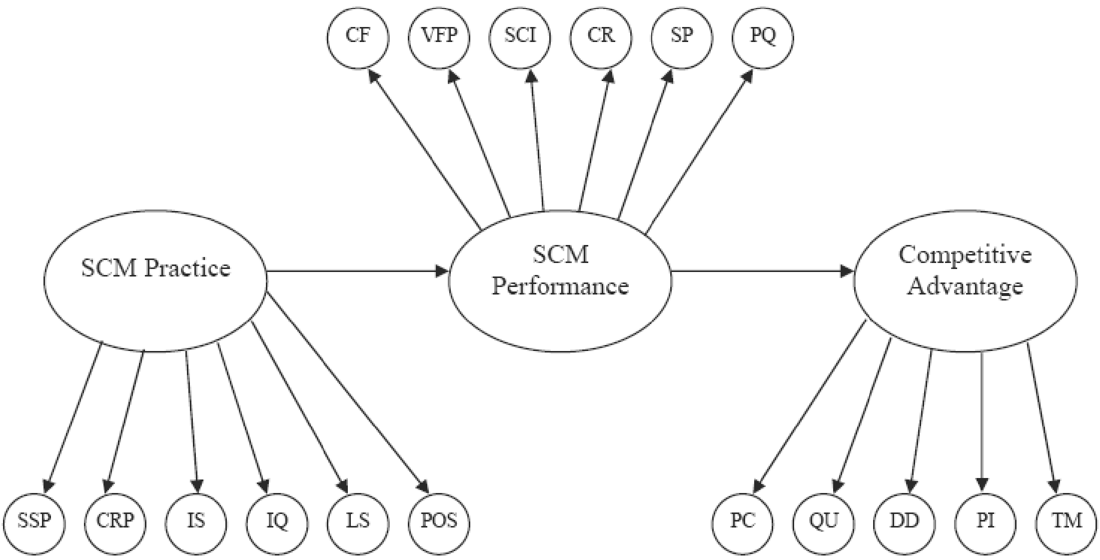


Figure 7: Illustrative model

As the results show, possible misspecification at the first order level could lead to drastic changes in the path coefficients and R square values. Assuming that the correct first order representation is reflective, wrongly specifying it as formative (that is going from Cases 1,2 and 3 to Cases 4, 5 and 6) resulted in ***deflation*** of path coefficients and R square values; this would lead one to erroneously conclude the absence of significant path relations and to possibly reject the model. Similarly, assuming that the correct first order representation is formative, wrongly specifying it as reflective would result in ***inflation*** of path coefficients and R square values; this would lead one to erroneously conclude the presence of significant path relations and to possibly accept an incorrect nomological model. Our results support and illustrate the discussions in Section 4. They underline the need for prior analysis of theoretical and domain related considerations while conceptualizing and modeling constructs as formative or reflective.

In the next section, we provide an overview of the PLS methodology for modeling of formative constructs and suggest guidelines for the same.

5. Overview of formative and reflective constructs in the OM literature

The issue of measurement model misspecification, has not been addressed in manufacturing and operations management research in any detail, to the knowledge of the authors. Recent literature though has initiated discussion on various caveats of the use of structural equation modeling (Shah and Goldstein, 2006). The relevance of this section is to find out the nature of construct modeling in OM research, i.e. whether predominantly reflective specifications have been tested by the researchers. Thus in this section we (a) comprehensively identify formative and reflective constructs that have been studied in the important OM journals. Moreover this section also tries to present the possible scale of measurement model misspecification. Since it is not possible to present a discussion on all of them, we have presented some of the majorly used reflective constructs and tried to suggest based on related literature how some of these could have been alternatively modeled.

5.1 Journal selection

We selected four journals which are widely considered to be the leading journals (Barman et al., 1991; Vokurka, 1996; Soteriou, 1998; Barman et al., 2001) in the disciplines of production, manufacturing and operations management, and which publish SEM based research. The journals are - Management Science (MS), Journal of Operations Management (JOM), Decision Sciences Journal (DS), Journal of Production and Operations Management Society (POMS). These journals have formed the basis of recent summative and review oriented articles involving SEM based research (Shah and Goldstein, 2006; e.g.).

5.2 Time frame and paper selection

We chose the time period 2002-2006 for our selection of articles, since we did not find relevant articles discussing formative and reflective constructs prior to that. We looked at all issues of the above mentioned journals during this time period (some 2007 issues were also included). We considered a total of 134 issues of the following journals JOM (31 issues), DS (21 issues), MS (61 issues) and POMS (21 issues). Each issue had multiple articles, for a total of approximately 800 articles.

Manual search of each paper followed its inclusion in the sample if the article had (1) a formative or reflective measurement model (using confirmatory factor analysis) or (2) a formative or reflective measurement model (using confirmatory factor analysis) along with a structural model. A total of 94 (JOM – 41, DS – 35, MS – 10, POMS – 8) articles met these criteria and formed the basis of our subsequent discussion. Three papers tested a formative measurement model. Six articles used the PLS software (Ranganathan and Sethi, 2002; Teigland & Wasko, 2003; Brown and Chin, 2004; Looney et al., 2006; Venkatesh and Agarwal, 2006; Modi and Mabert, 2007), and the rest used covariance based software (LISREL, e.g.) for analysis. The details are shown in Table 1a. The 94 articles yielded a total of 642 constructs, of which 586 were reflective first order constructs and 6 were formative first order constructs. There were 50 second order constructs, all of which were modeled as reflective. Details are shown in Table 1b.

5.3 Scale of misspecification

To identify the scale of misspecification we carried out a further literature search of the possible definitions of the constructs and its conceptualizations. Once they were obtained, two of the coauthors analyzed the possibilities of alternate specification (formative instead of reflective) based of the definition and conceptualization. This led to the list of constructs which had possible alternate specifications. This list was then cross verified by the other two coauthors and the final list was prepared. It was found that out of the 586 first order constructs, 254 could have alternate specifications (as high as 43%). Similarly for the second order constructs, 21 out of 50 were found to have possible alternative specifications (42%). These figures point out to the possibilities of measurement model re-specification and the scale of possible misspecification (Refer Table 5). The next subsection discusses some of the constructs obtained from OM literature and discusses the bases on which they were suggested to have alternative specifications.

Table 1a: Summary of the literature survey

Journal	Number of Articles	Methodology	Number of papers in which First Order Construct/s were tested	Number of papers in which Second Order Construct/s were tested	Number of papers in which a Path Model was tested
JOM	41	Reflective	40	14	29
		Formative	1	0	1
DS	35	Reflective	34	9	20
		Formative	1	0	0
MS	10	Reflective	9	0	7
		Formative	1	0	0
POMS	8	Reflective	8	1	5
		Formative	0	0	0
TOTAL	94	Reflective	91	24	61
		Formative	3	0	1
		Total	94	24	62

Note: JOM- Journal of Operations Management; DS- Decision Sciences Journal; MS – Management Science; POMS- Journal of Production and Operations Management Society

Table 1b: Summary of constructs

Journal	Reflective First Order Construct	Formative First Order Construct	Reflective Second Order Construct	Formative Second Order Construct	Total
JOM	272	1	28	0	301
DS	227	3	21	0	251
MS	57	2	0	0	59
POMS	30	0	1	0	31
TOTAL	586	6	50	0	642

Table 2: Summary of formative constructs in the literature

Journal	Author/s	First Order Construct/s Tested	Model	Methodology
JOM	Johnston et al., (2004)	Buyers Assessment of Performance	Formative	Partial Least Squares
DS	Brockman & Morgan, (2003)	Entrepreneurship Organization structure Cohesiveness	Formative Formative Formative	Covariance based (LISREL)
MS	Venkatesh and Agarwal, (2006)	Use Behaviour Purchase Behaviour	Formative Formative	PLS

Table 3: Constructs and sub-constructs used in the illustrative model

Second Order Construct	First Order Constructs	Code Used in Model
SCM Practice	Strategic Supplier Partnership	SSP
	Customer Relationship Practices	CRP
	Information Sharing	IS
	Information Quality	IQ
	Lean System	LS
	Postponement	POS
SCM Performance	Customization Flexibility	CF
	Volume and Product Flexibility	VFP
	Supply Chain Integration	SCI
	Responsiveness to Customers	CR
	Supplier Performance	SP
	Partnership Quality	PQ

Competitive Advantage	Price/Cost	PC
	Quality	QU
	Delivery Dependability	DD
	Product Innovation	PI
	Time to Market	TM

Table 4: Result of the trials

Case No	First Order Construct Type[7]	Second Order Constructs			Path Coefficients		R Square value	
		SCM Practice (scmprac)	SCM Performance (scmperf)	Competitive Advantage (compadva)	scmprac→ scmperf	scmperf→ compadva	scmperf	compadva
1	Reflective	Reflective	Reflective	Reflective	0.650	0.605	0.423	0.366
2	Reflective	Formative	Formative	Formative	0.670	0.642	0.449	0.412
3	Reflective	Formative	Reflective	Formative	0.662	0.620	0.438	0.385
4	Formative	Reflective	Reflective	Reflective	0.475	0.300	0.225	0.090
5	Formative	Formative	Formative	Formative	0.487	0.339	0.238	0.115
6	Formative	Formative	Reflective	Formative	0.488	0.312	0.238	0.097

Table 5: Suggested nature of misspecification

Journal	Reflective First Order Construct	Alternative Specification Possible	Reflective Second Order Construct	Alternative Specification Possible	Precentage of Alternative Specification
JOM	272	123	28	12	44.85
DS	227	98	21	9	42.63
MS	57	24	0	0	40.68
POMS	30	9	1	0	29.03
TOTAL	586	254	50	21	42.83

5.4 Brief discussion of constructs

In this subsection we identify some first and second order constructs, selected from the 642 constructs that we identified, which have been modeled reflectively in the OM literature. We then illustrate possible alternate modeling formulations for these constructs, basing our arguments on findings from other disciplines and on domain specific theoretical considerations.

To begin with, first order constructs comprising the **Technology Acceptance Model (TAM)** and its extensions, such as perceived-ease-of-use and perceived-usefulness of information systems have traditionally been modeled reflectively (Venkatesh et al., 2002; Somers et al, 2003; Kim and Malhotra, 2005; Abdinnour-Helm et al., 2005; Malhotra et al, 2006; Yi et al., 2006). However, researchers have, based on the definitions of these two constructs, suggested that they could be modeled formatively (Chin, 1998; Gefen et al., 2000). In this context, recent research has modeled some of these constructs formatively (Sánchez-Franco, 2006).

Satisfaction is another construct that has been modeled reflectively but lends itself to formative modeling as well. Satisfaction may be ***Job Satisfaction*** (Tesch et al., 2003; Janz and Prasarnphanich, 2003; Brown and Chin, 2004) or ***Customer Satisfaction*** (Goldstein, 2003; Kassinis

[7] First order constructs for all the second order constructs have similar type in a single case, either all reflective or all formative.

and Soteriou, 2003; Douglas and Fredendall, 2004; Marley et al. 2004; Babakus et al., 2004; Johnston et al., 2004; Froehle, 2006) or simply ***Satisfaction*** (Athanassopoulos and Iliakopoulos, 2003; Balasubramanian et al., 2003; Spreng and Page, 2003). All of these have been modeled reflectively. However, with respect to job satisfaction (Locke, 1969, p. 331) states that, "*a valid overall index of satisfaction would, in the present view, be a sum of the evaluations of all job aspects to which the individual responds*." This definition suggests a formative nature of this construct; Hartline and Ferrell (1996) have modeled job satisfaction as a formative construct and Fornell et al. (1996), Spreng et al. (1996) and Kristensen et al. (1999) have discussed the formative nature of the customer satisfaction construct.

The construct **Belief** (beliefs on investing in facilities and equipment, beliefs on usefulness, beliefs on learning, e.g) is another construct that we found to be modeled in a reflective manner (Froehle and Roth, 2004; Nahm et al., 2004). In contrast, marketing literature has previously discussed belief in a formative way (Ryan, 1982; Shimp and Kavas, 1984), which suggests opportunities for reconsidering the reflective formulation in the OM literature.

It is interesting to note that **Belief**, **Satisfaction** and the constructs related to **TAM** have a common conceptual basis in the Theory of Reasoned Action (Ajzen and Fishbein, 1973; Fishbein and Ajzen, 1975).

Knowledge has also been measured as a reflective construct (Calantone et al., 2002; Morgan et al., 2003; Fedor et al., 2003; Brockman and Morgan, 2003; Droge et al., 2003; Tu et al., 2006). Studies in business strategy and information systems literature have however hinted on both formative and reflective formulation of knowledge based on Activity Theory (Blackler, 1993) and Social Exchange Theory (Wasko and Faraj, 2005).

Research has modeled various aspects of **Performance** reflectively. These include Financial/Market Performance (Kaynak, 2003; Chen et al., 2004; Swink et al., 2007), Customer or Buyer Based Performance (Zahay and Griffin, 2004; Johnston et al., 2004), Product/Process Performance (Kaynak, 2003; Walace et al., 2004), and Supplier Performance (Prahinski and Benton, 2004). Johnston et al. (2004) however, measure performance (Buyers Assessment of Performance) as a formative construct. This implies that different aspects of performance can also be measured in a formative way.

Second order constructs that lend themselves to alternative formulation include **End User Computing Satisfaction**, **Flexible Manufacturing**, **Time-Based Manufacturing** and **Business Performance**. All of these have been modeled reflectively; domain related theoretical considerations lead us to possible arguments for formative modeling. Consider, for example the construct of **End User Computing Satisfaction**, which has first order dimensions of ***Content***, ***Accuracy***, ***Format***, ***Ease of Use*** and ***Timeliness*** (Somers et al., 2003). **End User Computing Satisfaction** can be argued to be an effect of its first order dimensions rather than their cause. In such a case it would be a formative construct. The construct **Flexible Manufacturing** (Zhang et al., 2003) can be posited to be the result of its first order dimensions - Machine Flexibility, Labor Flexibility, Material Handing Flexibility – rather than their cause. Hence it can be evaluated from a formative point of view. **Business Performance** (Cao and Dowlatshahi, 2005) can similarly be argued to be the aggregate of its first order constructs - Market Growth, Financial Performance, Product Innovation, and Company Reputation – if one argues that these dimensions determine business performance, rather than reflecting it. In that case the construct could be evaluated as formative. In a similar vein, one can review the second order construct **Time-Based Manufacturing Practices** (Tu et al., 2006) and argue for a formative model.

In this section we found that reflective measurement modeling has been predominant. The following section discusses the research implications with measurement model misspecification.

6. The implications for researchers in OM using measurement modeling

Reflective measurement models have been widely used in OM research and there is extensive mathematical and software support for their measurement and analysis. This is one of the reasons for which formative specification has not been followed to a high extent. However as our study points, there is a huge number of constructs (our study suggests around 42%) which could be alternately modeled and still would have theoretical support. This raises a big question in front of OM researchers. Should we try to have a relook at the way we were measuring constructs? Taking hint from section 5 we could observe that misspecification could be a possibility in practice and taking cue from section 4 we could also assume that misspecification may lead to erroneous results. Thus our study calls for a relook into measurement model specification and also offers a few guidelines which should be taken into note by the researchers before they embark upon measurement modeling in research.

7. Recommendations for future researchers

First and foremost, the theoretical and subject matter domain of the construct being studied should determine whether or not it is formative and would in turn influence the selection of appropriate indicators (Nunnally and Bernstein, 1994, p. 484). The items or indicators selected for measuring a formative construct should cover the entire scope of the construct and should be completely enumerated (Bollen and Lennox, 1991). Starting from such a standpoint the first step is to theoretically specify whether the construct is reflective or formative.

A more practical approach would also be to check for alternative model specifications and check for the scale of difference. As we found in our sample data possible misspecification could occur at the first order level or the second order level (provided second order constructs are considered). Both would have its own manifestations in the output coefficients and may render potential significant estimates as insignificant and vise versa. Thus one possibility open to the researcher is to try out alternate model specifications and to check out the range of difference in the output thus obtained. However, there is a note of caution. This approach would only be possible when the indicators on the construct could work as formative as well as reflective. Regarding proper selection of indicators, Mackenzie et al. (2005) have suggested that, an indicator will be formative provided (a) it defines a distinct characteristic of the construct, (b) any change in the its value is expected to explain changes in the construct, (c) it may or may not have a common theme (i.e. correlations) with other indicators, (d) removing an indicator may alter the conceptual domain of the construct and (e) it may not have the same antecedents and consequences as other indicators.

The researchers who would resort to formative modeling could try out the Partial Least Square based modeling instead of the more popular variance-covariance based structural equation modeling. The PLS approach lends itself well to the modeling of formative constructs, primarily for three reasons. First, using PLS, a researcher can test a formative latent variable in isolation. Second, it has less stringent restrictions on sample size, residual distributions and assumptions about normality of the data (Chin, 1998; Chin et al., 2003). Finally, recent availability of software (For a detailed review of PLS software, refer to Temme et al., 2006) based on the PLS approach (such as PLS Graph, VisualPLS, SMARTPLS, SPADPLS) has led to greater understanding of associated requirements and issues.

8. Conclusion

This paper presents a discussion of the use of formative measurement models in the context of SEM research in Operations and Manufacturing Management. We first highlighted theoretical and mathematical differences between formative and reflective measurement models. We then illustrated with a nomological model from the Supply Chain domain and using primary survey data, the impact of possible measurement model misspecification on model parameters and goodness of fit measures. Based on an extensive review of the OM literature, we identified the scale of measurement model misspecification and suggested alternative possible (formative) formulations. We also discussed the seriousness of the problem and suggested some operational guidelines for modeling formative constructs. While reflective constructs have been extensively modeled in the OM literature, the use of formative constructs has been relatively rare and software support has, until recently, not been extensively available. As a result of our study, we expect the research output obtained to be more grounded in theory and also mathematically correct. This paper therefore addresses a timely and important subject for SEM based research in OM.

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