International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713696255

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First published on: 02 July 2009

To cite this Article Roberts, Nicholas , Thatcher, Jason Bennett and Grover, Varun(2010) 'Advancing operations management theory using exploratory structural equation modelling techniques', International Journal of Production Research, 48: 15, 4329 — 4353, First published on: 02 July 2009 (iFirst)

To link to this Article: DOI: 10.1080/00207540902991682

URL: http://dx.doi.org/10.1080/00207540902991682

International Journal of Production Research
Vol. 48, No. 15, 1 August 2010, 4329–4353

Advancing operations management theory using exploratory structural equation modelling techniques

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(*Received 11 October 2008; final version received 20 April 2009*)

The structural equation modelling (SEM) technique has been touted as a useful tool for tightening links between theoretical and empirical operations management (OM) research. Despite SEM's increasing prominence in the field, leading scholars continue to call for a deeper infusion of theory into empirical OM research. To strengthen ties between theory and analysis in OM research, this study evaluates previous OM applications of SEM and identifies specific ways we can use SEM to advance operations management theory. Through judicious use of SEM techniques, we believe that OM researchers have the opportunity to confirm and extend existing theoretical frameworks. Further, we offer guidance on how to operationalise measurement models such that researchers accurately depict the causality of a construct. To demonstrate how to advance theory, we use an illustrative example of SEM in an OM context based upon data gathered from a survey of over 200 respondents.

Keywords: empirical research methods; general methodology; structural equation modelling; partial least squares; formative construct; measurement, sample size

1. Introduction

Operations management (OM) scholars have turned to structural equation modelling (SEM) to use survey data to examine complex theoretical models (Shah and Goldstein 2006). SEM is an analysis technique that allows one to simultaneously evaluate a structural model (i.e., relationships between constructs) and a measurement model (i.e., relationships between constructs and indicators) (Anderson and Gerbing 1988). When estimating the structural model, SEM takes into account the error embedded in each latent construct's measurement (Bollen 1989). By simultaneously estimating relationships among constructs as well as relationships between constructs and their indicators, SEM is thought to more rigorously conduct omnibus tests of theories that emulate real world processes than first generation techniques such as regression or exploratory factor analysis (Shah and Goldstein 2006). As a result, SEM's use in OM (Shah and Goldstein, 2006) strategic management (Shook *et al.* 2004), international business (Hult *et al.* 2006), and other business disciplines grew during the 1990s.

Because of SEM's relative sophistication, misapplications of the technique may limit its benefits. For example, many confirmatory SEM techniques calculate modification indices

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ISSN 0020–7543 print/ISSN 1366–588X online

DOI: 10.1080/00207540902991682
http://www.informaworld.com

that guide how to improve a model. However, without theoretical justification, data-driven, exploratory model revisions yield analysis that contribute little to understanding theoretical problems and guide future research in superfluous directions (MacCallum 1986). Further, SEM techniques exist which are useful for more exploratory, theory building research (Chin 1998a). For example, partial least squares (PLS) is an SEM tool which focuses on evaluating the predictive validity of relationships among constructs (Gefen *et al.* 2000). Lacking guidelines for when to use SEM techniques, their misapplication could be an acute problem in a field such as OM, where applications of SEM have been limited to largely confirmatory, covariance-based tools.

To promote SEM's use to enable better theory development, this study provides guidelines for, and an empirical illustration of, exploratory and confirmatory uses of SEM. In doing so, the study is not intended to be a 'textbook illustration' of SEM. Readers interested in a more in-depth review of SEM's theory and applications are referred to some excellent sources (Wold 1982, Long 1983, Sharma 1996, Kline 2005). Rather, we are particularly interested in illustrating issues related to using SEM techniques to build and test theoretical models. By providing guidance on the full range of SEM applications, we hope to aid OM researchers in realising the full potential of this powerful suite of analytic techniques for advancing theory.

2. Theory development in operations management

2.1 *SEM for theory building versus theory testing*

The importance of theory to advancing scientific knowledge in the OM field cannot be overstated. Bacharach (1989) defines theory as 'a statement of relations among concepts within a set of boundary assumptions and constraints' (p. 496). Theory development can be conceptualised as a dialectic or discourse between developing explanations for phenomena and the methods used to evaluate their validity (Weick 1995). Theory drives scholars' choice of methods through identifying appropriate levels of analysis, defining the nature of relevant constructs, and articulating explanations for relationships among constructs (Popper 1959, Kaplan 1964, Blalock 1969, Wacker 2004). In turn, limitations of research methods constrain researchers' ability to investigate phenomena and develop more sophisticated theory (Van Maanen *et al.* 2007). To effectively advance theory, one must judiciously select the tool used to identify or test relationships.

To provide a basis for subsequent discussion, we present a brief overview of SEM. SEM is a technique used to specify, estimate, and evaluate models of linear relationships among a set of observed variables in terms of an often smaller number of unobserved variables. SEM is widely diffused in various fields, such as management (Williams *et al.* 2003), information systems (Gefen *et al.* 2000), and operations management (Shah and Goldstein 2006). Figure 1 depicts a basic latent variable model. A circle is used to represent each of the four latent variables, and the boxes represent associated manifest or indicator variables. The relationships between the latent variables and their indicators are often referred to as a 'measurement' model, in that it represents an assumed process in which an underlying construct determines or causes behaviour that is reflected in measured indicator variables.

We note that the arrows go from the circles to the boxes, which is consistent with the process noted above. Thus, each factor serves as an independent variable in the measurement model, and the indicator variables serve as the dependent variables. Each

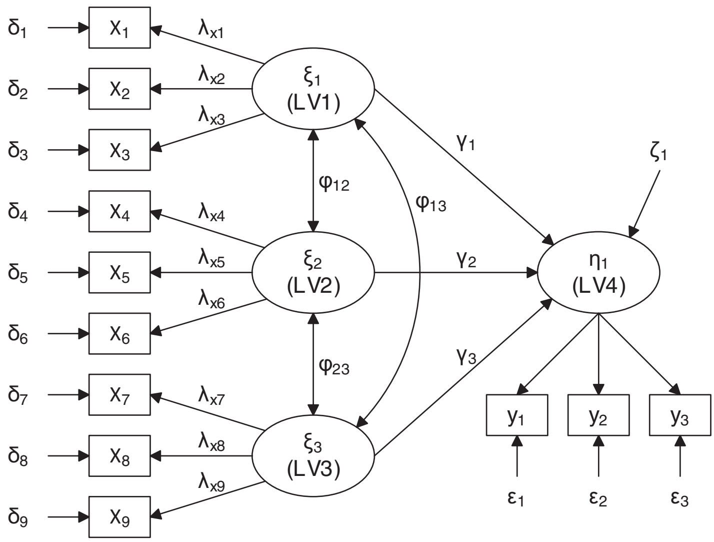

Figure 1. Basic latent variable model.

indicator is also potentially influenced by a second independent variable in the form of measurement error, and its influence is represented as a cause of the indicator variable through the use of a second arrow leading to each of the indicators. Finally, the model shown in Figure 1 includes correlations (double-headed arrows) among the three exogenous (independent) latent variables (LV1–LV3) and regression-like structural parameters linking exogenous and endogenous (dependent) latent variables (e.g., LV3 and LV4). The model also acknowledges that there is unexplained variance in the endogenous latent variable. The part of the overall model that proposes relationships among the latent variables is often referred to as the structural model. Table 1 includes terms used to describe a basic latent variable model.

When *building* theory, exploratory SEM techniques are useful for establishing relationships between constructs. Exploratory SEM techniques were developed to bridge the gap from identifying constructs to developing explanations for their inter-relationships (Bollen 1989). For example, partial least squares (PLS) is an SEM technique that was explicitly designed to establish that relationships exist and explain meaningful amounts of variance (see Chin 1998b for an in-depth review of PLS). Because of their emphasis on predicting causality and variation, exploratory SEM techniques such as PLS are well suited for analysis designed to build theory (Joreskog and Wold 1982).

When *testing* theory, confirmatory SEM techniques can be used to conduct rigorous tests of hypothesised relationships among constructs. Confirmatory SEM techniques were developed to evaluate the overall performance of models, i.e., they are designed to test broad theories (Bollen 1989, Bullock *et al.* 1994). Because confirmatory techniques rest on well-developed theory, they are well suited for extending, replicating, or adding nuances to tests of established theories. Confirmatory SEM techniques are particularly useful at this stage of theory development for three reasons.

(1) SEM techniques readily permit the testing of alternative theoretical models. When theory suggests competing models exist, scholars may use the same data to

Table 1. Definition of SEM terms[a].

Latent constructs		Latent constructs refers to abstract variables that can only be measured indirectly through their relationship to manifest variables, that are most often referred to as indicators.
Exogenous variables	(ε)	Latent constructs that are independent variables in all equations in which they appear.
Endogenous variables	(η)	Latent constructs that are dependent variables in at least one equation in which they appear.
Structural model		Refers to relationships among constructs. Typically, these are linear although some extensions of SEM allow for non-linear relationships.
Parameters		Refer to regression estimates of relationships between constructs in a structural model.
Gamma	(γ)	Refers to a regression estimate of a relationship between an independent and a dependent construct in a structural model.
Beta	(β)	Refers to a regression estimate of a relationship from one endogenous variable to another.
Phi	(φ)	Refers to relationships among constructs that are allowed to covary freely. This covariance is a function of shared predictors of exogenous constructs that are not explicitly modelled in a structural model.
Zeta (error)	(ζ)	Refers to error in estimates of relationships among constructs. Typically, error terms are assumed to be uncorrelated.
Measurement model		Refers to the relationship among constructs and manifest variables.
Manifest variables		Latent constructs are typically associated with no fewer than three manifest variables. The collection of relationships among latent constructs and their specific, manifest indicators are the measurement model. Refers to indicators of latent constructs in a structural model. Indicators of exogenous constructs are typically referred to as X. Indicators of endogenous constructs are typically referred to as Y.
Loadings	(λ)	Refers to the relationship between indicators and the common factor associated with the latent construct.
Weights	(γ)	Refers to the relative contribution of a formative indicator to the latent construct. Empirically, they are indistinguishable from parameter estimates, hence the similar notation.

Note: [a]Bollen (1989) provides a detailed explanation of terms used in structural equation models.

examine which rival explanation best explains variance in data (Anderson and Gerbing 1988).

(2) Results of SEM analysis such as modification indices can provide insight into plausible alternative explanations for relationships among constructs. By inspecting modification indices, scholars can determine whether the data suggests that alternative theoretical models provide a stronger explanation for a phenomenon and identify new directions for developing theory (Bollen 1989).

(3) If properly reported, SEM results are replicable and reusable. As the understanding of a phenomenon advances, scholars can conduct independent tests to confirm findings as well as use such analysis as a starting point for testing new explanations for the relationship among constructs (Hubbard *et al.* 1998, Frohlich and Dixon 2006). While true replication requires collecting new data (Hubbard *et al.* 1998, Frohlich and Dixon 2006), SEM provides opportunities to independently confirm results and evaluate alternative models as a means for OM researchers to more quickly advance theory.

Collectively, when analysis suggests that extant theories provide an inadequate explanation for an existing or new phenomenon, opportunities arise for researchers to seek alternative explanations (i.e., develop new theory) (Alvesson and Karreman 2007).

To assess SEM's use, we reviewed empirical research published between 1995 and 2007 in leading OM journals[1]. Due to our interest in understanding applications of SEM, we restricted our review to empirical OM research and, by extension, the latter stages of theory development (building, testing, and extension/refinement). We identified 165 empirical papers that used SEM techniques during this period. Of these studies, 159 (96% of all studies) employed confirmatory SEM techniques. *Our findings suggest confirmatory SEM techniques are being used to test and develop theoretical models*. Because analytical tools are useful for not only verifying results but also moving a concept's development forward (Alvesson and Karreman 2007), our review suggests that opportunities exist for using a broader range of SEM to inform theory development.

2.2 *Construct validity: the foundation of empirical analysis*

When selecting SEM techniques, OM researchers must consider not only theory that explains causality among constructs (Wacker 1998), they must also direct attention to theory about causality among constructs and indicators (Wacker 2004). In addition to specifying relationships between theoretical constructs (referred to as the structural model in SEM) (Bagozzi and Fornell 1982), theory guides how to conceptualise and operationalise constructs (referred to as the measurement model in SEM). Without this auxiliary theory, the mapping of theoretical constructs onto empirical phenomena is ambiguous, and primary theories cannot be meaningfully tested (Costner 1969, Blalock 1971, Wacker 2004). When theory guides construct operationalisation, OM scholars more quickly advance our understanding of phenomena (Ho *et al.* 2002).

Theory defines the causality between a construct and its indicators. Causality refers to whether a construct is reflected or formed by its indicators. Reflective constructs are viewed as causes of indicators, meaning that variation in a construct leads to variation in its indicators (Bollen 1989). As a result, reflective indicators represent reflections or manifestations of the overarching reflective construct. On the other hand, formative constructs are formed or induced by their indicators (Fornell and Bookstein 1982). For example, although 'firm performance' is often modelled as reflective (e.g., Das *et al.* 2000, Carr and Pearson 2002), one cannot logically expect return on investment, profit as a percentage of sales, and net income before taxes to covary (because they have diverse sources such as firm history or current market conditions). In the case of formative constructs, indicators are viewed as the cause, or source, of construct's value. Although the nature and direction of relationships between constructs and indicators have been discussed in the literature on construct validity and structural equation modelling

(Blalock 1971, Bollen 1989), little attention has been given to the formative/reflective distinction in OM research (Shah and Goldstein 2006). Our review of SEM in OM research suggests that 97% of all studies modelled constructs as reflective. In our review, only four studies modelled at least one formative construct. *This clearly under represents the true theoretical nature of constructs in that frequently researched constructs (such as firm performance) should be conceptualised as formative*. There are a number of ostensible reasons for the lack of formative constructs in OM research. Some of these reasons include:

(1) Formative constructs are not readily supported by software (Gefen *et al*. 2000).
(2) Researchers have few conceptual criteria for determining whether constructs should be specified as reflective or formative (Diamantopoulos and Winklhofer 2001, Diamantopoulos *et al*. 2008).
(3) There is a lack of consistent standards for assessing psychometric properties of such measures (Bollen 1989, Bagozzi 1994).

Because our review suggests that there are opportunities to more effectively use SEM, we provide a detailed review of issues related to using SEM to model causality between constructs and indicators[2].

3. Towards better construct representation

Reflective constructs cause their indicators, meaning that variation in a construct leads to variation in its indicators (Bollen 1989). Reflective measurement underpins classical test theory (Lord and Novick 1968), reliability estimation (Nunnally and Bernstein 1994), and factor analysis (Harman 1976), each of which treats an indicator as a function of a latent variable (i.e., construct) plus error (Churchill 1979). In the OM field, research on scale or instrument development focuses on reflective constructs (cf. Ahire *et al*. 1996, Hensley 1999). Figure 2 depicts the relationship between constructs and their indicators. Formative indicators have several theoretical properties that distinguish them from conventional reflective indicators (see Table 2).

When defining a reflective construct, one views indicators' value as dependent on a latent variable (Nunnally and Bernstein 1994):

$$y_i = \lambda_{i1}\eta_1 + \varepsilon_1, \tag{1}$$

where y_i is the ith indicator, η_1 is the latent variable that affects it, ε_1 is the measurement error for the ith indicator, and λ_{i1} is the coefficient giving the expected effect of η_1 on y_i.

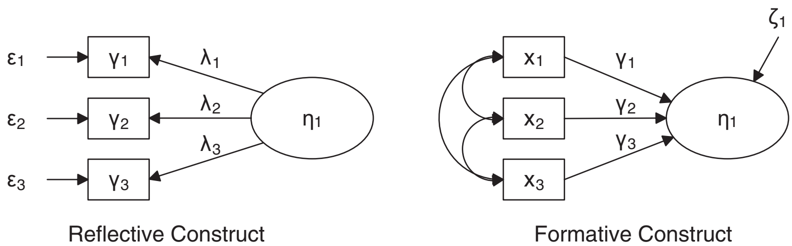

Figure 2. Reflective and formative constructs.

A reflective approach suggests that the underlying construct causes its indicators. For example, Escrig-Tena and Bou-Llusar (2005) model flexibility as a function of three indicators that direct attention to how quickly a firm is able to change. Although the indicators direct attention to different processes, their values are a function of the underlying latent construct of firm capability to quickly change processes. Because the latent construct causes indicators' values, its measures should be internally consistent, i.e., correlated, and their validity can be evaluated through traditional measures of convergent validity (e.g., Cronbach's Alpha) (Nunnally and Bernstein 1994).

When defining a formative construct, one views the indicators as causing, or inducing, change in the latent variable (Blalock 1971, Edwards and Bagozzi 2000):

$$\eta_1 = \gamma_1 x_1 + \gamma_2 x_2 + \cdots \gamma_n x_n + \zeta_1, \tag{2}$$

where η_1 and all xs are deviation scores, the deviation scores do not covary with the latent variable's disturbance term (ζ_1), and the disturbance term equals zero (all of the variance in the latent variable is accounted for by its indicators) (Bollen and Lennox 1991)[3]. An example of a formative construct in OM research is entrepreneurial environment, which is formed by education level and industry experience (Raymond and St-Pierre 2005). Theoretically, formative indicators are assumed to be uncorrelated and cannot be evaluated using traditional measures of convergent validity (Barclay *et al*. 1995).

In terms of theory, indicators' domain space is a key distinction between reflective and formative constructs. Because reflective constructs' indicators occupy the same domain space, they can be used interchangeably without undermining measurement of the construct. In contrast, removing a formative indicator implies removing a theoretically meaningful part of the construct (Bollen and Lennox 1991) (see Figure 3). Consider firm performance: if one solely relied on return on investment (ROI) and net present value (NPV), and failed to capture profit, one would not capture the theoretical meaning of the construct (Das *et al*. 2000, Carr and Pearson 2002). Although theoretically uncorrelated, in practice, formative indicators often covary. Again, consider firm performance: while

Table 2. Conceptual differences between formative and reflective indicators.

Concept	Formative indicators	Reflective indicators
Causality	Formative indicators are viewed as causes of constructs (Blalock 1971). The construct is formed or induced by its indicators (Fornell and Bookstein 1982).	Constructs are viewed as causes of reflective indicators (Bollen 1989). Reflective indicators represent manifestations of a construct (Fornell and Bookstein 1982).
Interchangeable	Not interchangeable – 'omitting an indicator is omitting a part of the construct' (Bollen and Lennox 1991, p. 308).	Interchangeable – the removal of an indicator does not change the essential nature of the construct. Although every indicator need not be the same, researchers need to capture the domain space of the construct (Little *et al*. 1999).
Validity	Indicators are exogenously determined; hence, correlations are not explained by the measurement model (Bollen 1989).	Validity of indicators can be assessed through the measurement model (Bagozzi *et al*. 1991).

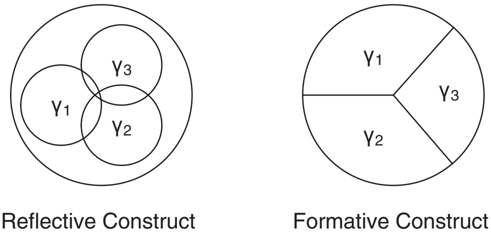

Figure 3. Indicators and the domain space of reflective and formative constructs.

ROI, NPV, and profit may not covary, it would be surprising if they were not somewhat correlated (cf. Das *et al.* 2000, Carr and Pearson 2002). What is important to understand is that, even if correlated, each indicator is necessary for measuring a formative construct, and removing such an indicator leaves part of the construct unmeasured (Bollen and Lennox 1991).

4. Illustration: information technology and inter-firm cooperation

In this section, we illustrate issues related to using exploratory (component-based) techniques and explain them in light of how confirmatory (covariance-based) techniques handle similar issues. We do so for three reasons. First, because PLS is underutilised in OM research, we present analysis using it to illustrate decisions and issues related to its use, and take care to note how it differs from component-based SEM approaches. Second, in the methods literature, articles which provide advice on (cf. Hauser 1971, Joreskog and Goldberger 1975, Diamantopoulos and Winklhofer 2001), and critiques of (Borsboom *et al.* 2003, Ping 2004, Wilcox *et al.* 2008), using confirmatory SEM techniques such as EQS or AMOS exist for how to model formative constructs in SEM; however, scant practical advice exists in the methods literature for how to use exploratory SEM techniques such as PLS (Chin 1998a, Jarvis *et al.* 2003, Roberts and Thatcher 2009). Third, while covariance based SEM approaches are not able to estimate models with a formative endogenous construct because they are statistically under-identified (cf. Hauser 1971, Joreskog and Goldberger 1975, Diamantopoulos and Winklhofer 2001), components based SEM approaches can estimate such models. Next we briefly describe our illustration.

4.1 *Theoretical model*

Understanding influences of inter-firm cooperation and interdependence has been of interest to organisational and OM scholars (Heide and Miner 1992, Fynes *et al.* 2005). Information technology (IT) may be one source of interdependence (Kim and Narasimhan 2002). Frequently, manufacturers and suppliers expend substantial effort, money, and time developing information systems that manage activities such as inventory control or invoicing. When firms use IT to automate interaction, sunk costs (i.e., IT investments) may predispose them to cooperate at higher levels (Bensaou and Anderson 1999). Hence, we examine the following research question: *does the degree of automation enabled by information technology present in the relationship between manufacturers and suppliers enhance the level of voluntary information exchange and shared problem solving?*

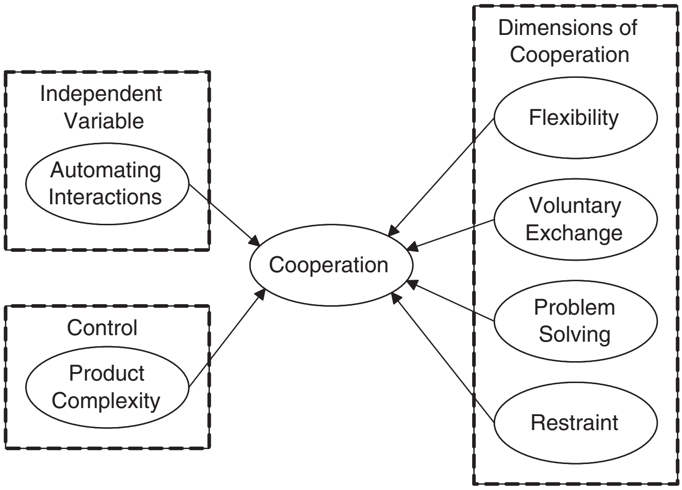

Figure 4. Research model.

Our research model suggests that automating interactions with IT will have a direct positive influence on cooperation between manufacturers and suppliers (Zaheer and Venkatraman 1994, Grover *et al.* 2002) (see Figure 4). Also, because product complexity may influence firms' ability to exchange information and jointly solve problems, we introduce it as a control variable (Sanchez and Mahoney 1996).

4.2 *Sample*

Data was gathered from organisational buyers as part of a larger study on buyer-supplier relationships. To limit industry effects, data was restricted to dyadic exchange relationships of electrical equipment manufacturers and their component suppliers. An initial set of 1000 purchasing managers was obtained from a professional information service affiliated with a number of magazines. These individuals were asked to identify a single supplier that:

(1) Provides an important input (electronic component) to production.
(2) Has completed multiple transactions with the company.
(3) Mainly provides a particular type of component rather than a variety of components.
(4) Has an electronic linkage with the company (e.g., electronic data interchange etc.).

Respondents filled out our instrument with respect to the dyadic relationship involving the selected supplier and component. Of the 730 organisations that satisfied these criteria, 203 (27%) responded. Appendix 2 presents our construct measures.

We use this data to provide an empirical illustration of PLS (using PLSGraph, a component-based SEM software package) estimation techniques as part of our discussion of how to use SEM when building and testing theory in OM research.[4]

4.3 *Theory building vs. theory testing: choosing an SEM technique for primary theory*

Conceptually, the broad classes of SEM techniques map to exploratory and confirmatory research – with a variance based focus on individual relationships being more appropriate for theory development, and the covariance based focus on 'fit' of global models to data being more appropriate for theory testing. Variance based, exploratory SEM techniques establish that relationships exist. For example, using an iterative partial least squares (PLS) techniques estimate parameters between segments of a model (Löhmoeller 1984), PLS focuses on maximising the variance explained by the structural model (Wold 1982). While holding constant other parameters and minimising residuals' variance, PLS estimates standardised regression coefficients between exogenous and endogenous variables (cf. Barclay *et al.* 1995). Also, PLS is well-suited to handling problematic features of data sets used to develop theory. For instance, because of its component based approach, PLS requires relatively small samples. Further, to establish the significance of relationships among constructs, PLS uses exact tests based on bootstrapping or jackknifing that are relatively robust to non-normal distributions. Because exploratory research is often characterised by using small, non-normal samples to establish that relationships exist, *PLS is a useful tool for the early stages of theory development*.

In contrast to exploratory, variance based approaches, covariance based SEM techniques conduct omnibus tests of theoretical models. Most frequently using maximum likelihood (ML) estimation techniques, confirmatory SEM techniques use an iterative procedure to optimise relationships described in a model. When improvement in the relationships approaches zero, the model 'has converged' and the resulting model-implied covariance matrix is compared to the empirical covariance matrix (Joreskog and Wold 1982). When the matrices are consistent (i.e., fit), the structural model is considered a plausible explanation for relations between the measures. Given the emphasis on comparing the model implied and actual covariance matrix, *confirmatory SEM techniques are useful for the latter stages of theory development*.

4.3.1 *Contrasting metrics for exploratory and confirmatory SEM*

Consistent with the different emphasis of the techniques described above, metrics for assessing variance based and covariance based SEM techniques focus on different elements of theory. Metrics for variance based SEM techniques focus on assessing relationships between constructs and their implications. To evaluate a relationship estimated in PLS, one uses t-statistics to assess the significance of standardised regression coefficients and examines the size of explained variance (R^2) in endogenous variables. To formally test whether the addition of a path results in meaningful change in a dependent variable, one can calculate an F-test for predictive relevance (Chin 1998b). Because variance based techniques do not offer global metrics of model fit, they should not be used to evaluate a model's overall performance.

Where variance based SEM techniques assess individual relationships and their influence, metrics for covariance based SEM techniques focus on confirming theory i.e., a model's overall performance. Covariance based SEM techniques estimate measures of model 'fit' (i.e., the ability of an implied covariance matrix to reproduce the observed covariance matrix in the data). Fit indices are either absolute or incremental (Bollen 1989). Absolute fit indices, such as chi-squared tests, the goodness of fit index (GFI), or adjusted goodness of fit index (AGFI) evaluate the degree to which the model reproduces the observed covariance matrix. Incremental fit indices such as the comparative fit index (CFI), normed fit index (NFI) and standardised root mean square residual (SRMR) assess the relative improvement in fit when the model is compared with a restricted, nested baseline model (Hu and Bentler 1998). When a model performs well on each dimension of fit, analysis provides evidence that the primary theory being tested is valid and provides a useful foundation for future research (Boomsma 2000, McDonald and Ho 2002, Kline 2005).

Although well-suited for different stages of theory development, scholars often misappropriate confirmatory, covariance based techniques and use them for theory building. An ostensible reason for this problem is that covariance based SEM analysis offers the opportunity to go beyond global model 'fit' and examine the significance and variance explained by individual relationships. Doing so is important, because empirically it is possible for a covariance based SEM technique to yield a good fit for a model, yet it is also possible for many paths to be misspecified or not explain significant variance in endogenous constructs. However, even when adhering to prescriptions to conduct specification searches (cf. Shah and Goldstein 2006), OM scholars need to keep in mind the purpose of confirmatory applications of covariance SEM techniques – which is to assess the validity of theoretical explanations for networks of relationships. While it is appropriate to glean insight into alternative explanations through specification searches, such insight should be rooted in, as well as extend, theoretical understanding of a phenomenon. Lacking a robust foundation, covariance based SEM analysis driven by specification searches does little to advance theory.

4.3.2 *Empirical illustration*

To illustrate principles related to advancing OM theory using SEM, we first assessed the theory underpinning our empirical illustration. While the relationship between complexity and cooperation is well established, the direct effect of automating interactions with IT on cooperation between buyers and suppliers has received limited theoretical and empirical attention (e.g., Carr and Pearson 2002). Within the literature on supply chains, research has found that IT influences the choice of mechanisms used to coordinate relationships (Zhu *et al.* 2006). However, less attention has been paid to the direct effects of automating interaction on cooperation (i.e., facets of cooperation itself, not the mechanism used to enable cooperation).

Given the limited theoretical and empirical attention to the proposed relationship, variance based SEM techniques are best suited to establishing whether the relationship between automating interactions with IT and cooperation is significant and explains meaningful amounts of variance. We used PLS to assess the relationship (see Figure 5). First, we estimated the direct effects of product complexity and automating interactions on cooperation. We found that product complexity is significantly related to cooperation ($\beta = 0.28$, $p < 0.05$) and that automating interactions with IT did not significantly relate to cooperation ($\beta = 0.14$, n.s.). Also, we found that the hypothesised relationships predicted 7.4% of the variance in cooperation. Further, an F-test of predictive relevance suggested that adding automating interactions with IT did not explain a significant amount of additional variance in cooperation among buyers and suppliers ($\Delta R^2 = 0.01$). Hence, while a preliminary theory suggested that a significant relationship may exist between automating interactions with IT and cooperation, our analysis using a variance based SEM technique suggests that this relationship is neither significant nor does it explain meaningful variance in cooperation. By providing evidence that this relationship is not significant, exploratory analysis using variance based SEM allows researchers to pursue more fruitful directions for explaining sources of inter-firm cooperation.

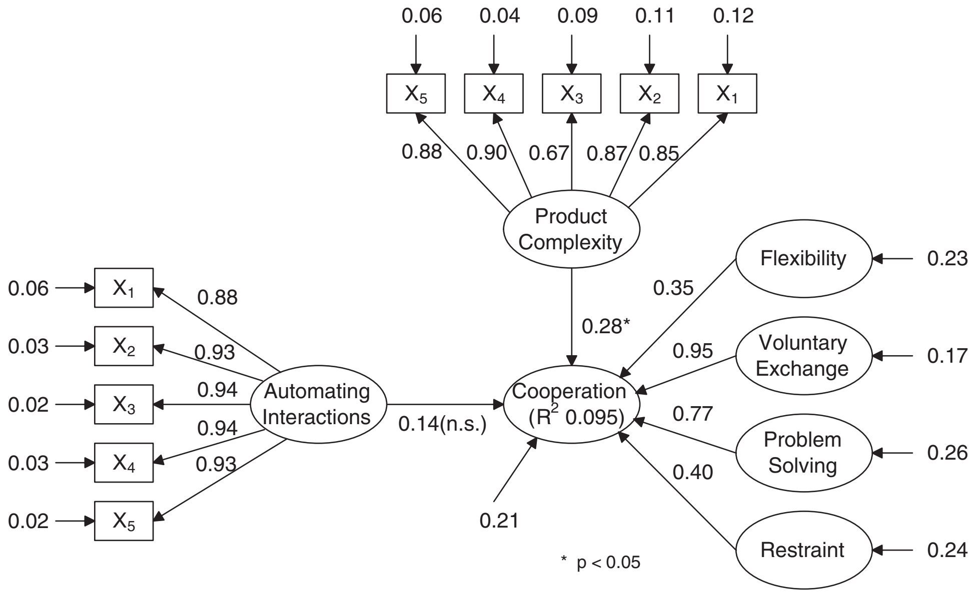

Figure 5. PLS solution for measurement and structural models.

4.4 *Causality of constructs*

Causal relationships between constructs and their indicators should also influence the choice among SEM techniques. Although formative constructs may be modelled in exploratory and confirmatory SEM techniques, issues related to model identification render each technique best suited for estimating different measurement models. Models are identified when it is 'theoretically possible to derive a unique estimate of each parameter' (Kline 2005, p. 105). Formative constructs often contain unidentified parameters, thereby creating a model identification problem (MacCallum and Browne 1993, p. 537). Models that are not identified are not meaningfully interpretable because they contain parameters whose values are arbitrary. Taken in isolation, the formative construct's measurement model in Figure 4 is statistically under identified (Bollen and Lennox 1991).

To identify a model with formative constructs, theory suggests: (1) placing formative constructs within a larger model; and (2) specifying at least two paths from the formative construct to reflective constructs (MacCallum and Browne 1993, Diamantopoulos and Winklhofer 2001). Lacking more than one path to a reflective construct, the residual variance of the formative construct will be under identified and must be fixed at zero – resulting in a potentially inaccurate depiction of the relationships among constructs. Because exploratory techniques such as PLS do not require identification, they may be used to *estimate models that theory suggests are comprised of formative constructs or use a formative construct as the dependent variable*. In contrast, confirmatory techniques require identification of the measurement model and are *well suited for models that: (1) incorporate reflective constructs; and (2) do not use a formative construct as the ultimate dependent variable.*

4.4.1 *Empirical illustration: causality*

When determining whether a construct is formative or reflective, scholars should use theory, not empirical analysis, to define the nature of a construct. While one could offer

Table 3. Decision rules to model constructs as formative or reflective[a].

Decision rule	Formative construct	Reflective construct
Causality		
Do the indicators define the construct or are they manifestations of the construct?	Indicators define the construct	Indicators manifest the construct
How do changes occur in the construct?	Changes in the indicators cause changes in the construct	Changes in the indicators do not cause changes in the construct
Indicator interchangeability		
Are the indicators interchangeable?	Indicators need not be interchangeable	Indicators should be interchangeable
Do the indicators have a common theme?	Indicators often employ different themes	Indicators have a common theme
Would dropping one of the indicators alter the conceptual domain of the construct?	Dropping an indicator may alter the conceptual domain of the construct	Dropping an indicator should not alter the conceptual domain of the construct
Covariation among indicators		
Do the indicators covary with one another?	Indicators may covary, but they need not necessarily covary	Indicators are required to covary with one another
Nomological network		
Are the indicators expected to have the same antecedents and consequences?	Indicators are not required to have the same antecedents and consequences	Indicators are required to have the same antecedents and consequences

Note: [a]Based on Jarvis *et al*. (2003).

empirical evidence that a construct is formative or reflective (e.g., indicators do not covary), theory should be the ultimate arbiter of the relationship between a construct and its indicators. One can apply three basic theory-driven guidelines when considering the causal relationship between a construct and its indicators (see Table 3).

(1) *Consider whether theory suggests a construct is a function of, or creates variance in, its indicators*. Cooperation is a function of four theoretically distinct sources: (a) flexibility in the relationship; (b) voluntary exchange of useful information; (c) extent of shared problem solving; and (d) restraint in the use of power (see Figure 4) (Heide and Miner 1992). In contrast, automating interactions with information technology is reflective. Conceptually, the degree to which buyers and suppliers agree to automate interactions with IT drives how they use IT to exchange information. In the case of cooperation and automating interactions with IT, theory clearly defines the relationship among the constructs and their indicators.

(2) *Determine whether a construct is formative or reflective by assessing the interchangeability of its indicators*. In the case of cooperation, its indicators are not interchangeable, because failing to measure one of cooperation's dimensions changes the substantive meaning of the overarching construct. However, one could remove an indicator of automating interactions with IT and remain faithful to the

conceptual definition of the construct. Thus, consistent use of indicators with secondary theory serves as a useful ancillary test of whether a construct is formative or reflective.

(3) *Examine indicators' convergent and nomological validity through the lens of secondary theory*. Indicators of a formative construct need not covary nor share antecedents or consequences. Although conceptually related, cooperation's indicators such as voluntary exchange of information and restraint in the use of power have distinct theoretical foundations and well-defined relationships with different constructs (Heide and Miner 1992). In contrast, reflective constructs' indicators should share domain space within a nomological network. Whether modelled together or separately, automating interactions with IT's indicators should demonstrate consistent relationships with other constructs in their nomological network.

Based on our discussion of metrics rooted in theory, we model cooperation as formative (i.e., it is a function of four indicators), and automating interactions with IT as being reflected by its indicators. Further based on our metrics, we model product complexity and the four dimensions of cooperation (flexibility, voluntary exchange, problem solving, and restraint) as reflective constructs. Theoretically, cooperation's dimensions are the source of variation in their indicators. It is useful to note that the distinction between dimensions of formative constructs and hypotheses-based antecedents must be made on theoretical/conceptual grounds. In this case, 'automating interactions' is a mechanism, 'product complexity' is a characteristic of the product and is clearly exogenous, and both of these constructs are not facets of cooperation.

4.4.2 *Empirical illustration: formative and reflective constructs*

Having used secondary theory to establish the causality of relationships between our constructs and their indicators, it is important to understand the metrics used by variance and covariance based SEM techniques to evaluate measurement models comprising formative and reflective constructs. Because our ultimate dependent variable is a formative construct (which would result in a statistically under-identified model using covariance-based techniques), we used PLS to estimate the relationship between automating interactions with IT and cooperation. One assesses the weight of each indicator when using variance based SEM techniques. If an indicator's weight is significant, it contributes to the measurement of the formative latent construct (Chin 1998b). In our empirical illustration, each of the weights of cooperation's indicators was significant (see Figure 5). Even if an indicator's weight is not significant, the decision to keep or discard a formative indicator should hinge on its theoretical implication – if it is part of a construct's conceptual definition, it should be kept (Diamantopoulos and Winklhofer 2001). For reflective constructs, variance based SEM techniques rely on heuristics similar to evaluating indicators in covariance based SEM (i.e., indicator loadings, composite reliabilities, and average variance extracted) (Chin 1998b). If one were to model the second-order construct as reflective, one would simply reverse the causality of the indicators and estimate a structural and measurement model. Given that cooperation is not reflective, we use its reflective dimensions to illustrate how to evaluate a reflective construct. All of our dimensions' indicators loaded significantly and at acceptable levels on automating interactions with IT, providing evidence of convergent and discriminant

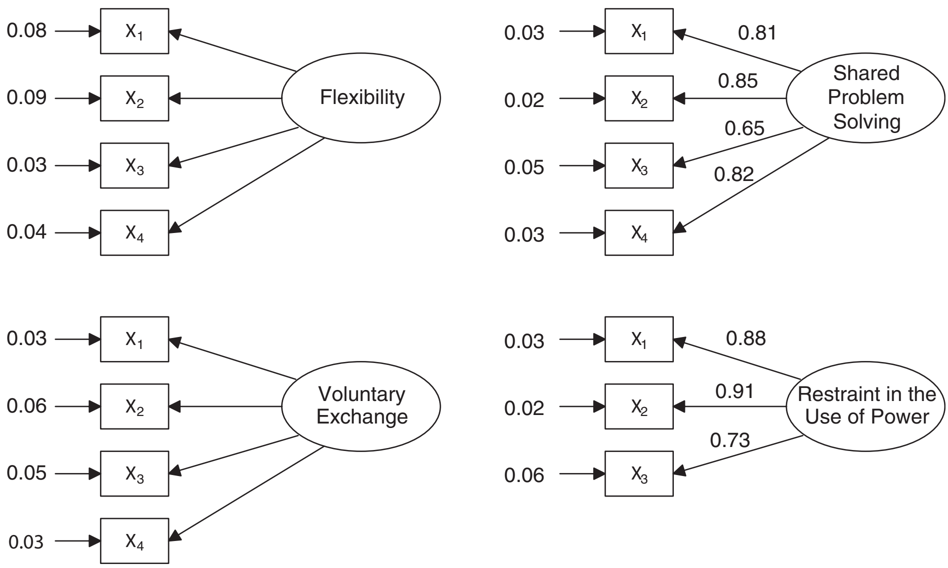

Figure 6. PLS solution for cooperation measurement model.

Table 4. Research model reliabilities and correlation of constructs.

Constructs	Mean (std dev.)	Composite reliabilities	Correlation of constructs and average variance extracted[ab] (1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Flexibility in the relationship	5.14 (1.00)	0.72	**0.70**						
(2) Voluntary exchange of power	5.73 (1.04)	0.87	0.48	**0.79**					
(3) Extent of shared problem solving	5.49 (1.02)	0.87	0.50	0.68	**0.79**				
(4) Restraint in the use of power	5.78 (1.30)	0.78	0.36	0.56	0.59	**0.84**			
(5) Automating Interactions with IT		0.97	0.02	0.13	0.19	0.07	**0.95**		
(6) Product complexity	4.11 (1.56)	0.90	0.13	0.24	0.14	0.09	0.09	**0.84**	
(7) Cooperation	2.81 (2.02)	0.96	0.70	0.85	0.87	0.77	0.13	0.21	**0.79**

Note: [a]Estimated using PLSGraph;
[b]Diagonal elements in the 'correlation of constructs' matrix are the square root of the average variance extracted. For adequate discriminant validity, diagonal elements should be greater than corresponding off-diagonal elements.

validity (see Figure 6). Further, construct reliabilities and average variance extracted confirmed that the indicators were convergent and discriminant (see Table 4).

When the ultimate dependent variable is not formative, methodologists suggest using the multiple indicators and multiple causes (MIMIC) approach to covariance based

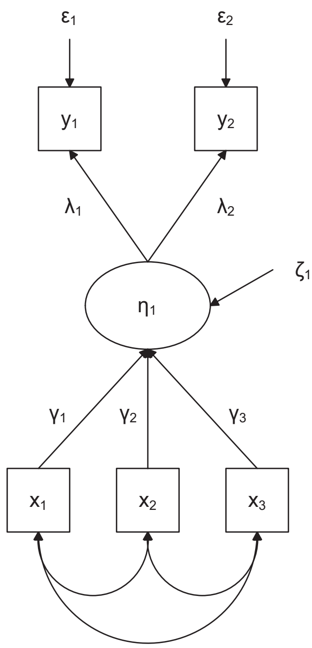

Figure 7. MIMIC model.

analysis as a means to assess models integrating formative and reflective constructs (cf. Hauser 1971, Joreskog and Goldberger 1975, Diamantopoulos and Winklhofer 2001). In this model, the formative indicators, x_i, act as direct causes of the latent variable, η_1, which is indicated by one or more reflective measures, y. The inclusion of reflective measures renders the model identified (Bollen 1989) (see Figure 7).

When evaluating a MIMIC model, one does not assess the loadings nor weights of individual indicators of formative constructs (Diamantopoulos and Winklhofer 2001); rather one focuses on the fit of the overall model. Model fit can be assessed through using standard heuristics of fit, such as the model chi-square, CFI, GFI, NFI, or root mean squared error of approximation (RMSEA) (Hu and Bentler 1998, Gefen *et al.* 2000). Acceptable fit of the overall model provides support for the set of indicators forming the construct. For reflective constructs, confirmatory SEM techniques adhere to well-established heuristics described in prior research (cf. Long 1983). Hence, in a manner similar to assessing the structural model, covariance based approaches to estimating formative constructs emphasise global fit of a model, not the significance of individual relationships embedded within the measurement model.

4.5 *Consequences of model misspecification: Type I and Type II errors*

Misspecifying relationships in measurement models increases the risk of making Type I or Type II errors in tests of structural models. A Type I error declares a path significant when it is really non-significant (a false positive); a Type II error declares a path non-significant when it is really significant (a false negative). Type I and Type II errors resulting from misspecified relationships constrain our ability to advance theory (Edwards and Bagozzi 2000). The danger of a Type I error is that we may build new theories based on prior

Table 5. Conditions under which errors occur if constructs are misspecified[a].

Error	Conditions under which error is likely to occur
Type I	• Formative construct is endogenous • Structural path emanates from formative construct • Sample size is high (i.e., 500) • Moderate to high correlation among formative indicators (i.e., 0.4 or higher inter-item correlations) • Can occur regardless of whether the model is specified correctly (i.e., formative) or incorrectly (i.e., reflective)
Type II	• Formative construct is endogenous • Structural path leads to formative construct • Sample size is low (i.e., 250) • Moderate to high correlation among formative indicators (i.e., 0.4 or higher inter-item correlations) OR • Formative construct is endogenous • Structural path leads to formative construct • Sample size is high (i.e., 500) • High correlation among formative indicators (i.e., 0.7 or higher inter-item correlations)

Note: [a]Based on MacKenzie *et al*. (2005), and Petter *et al*. (2007).

research that finds support for a given relationship that does not exist. The danger of a Type II error is that interesting, valuable research may not be published if many relationships in the model are found to be non-significant.

In light of our suggestion that theory advances more quickly when one investigates alternative structural models, it is important to note that atheoretically respecifying models can lead to Type I and Type II errors (MacCallum 1986). With each model respecification, the statistical probability that one makes a Type I or Type II error significantly increases with the number of model modifications and fit indices selected to evaluate models (MacCallum 1986, MacCallum *et al*. 1992). Also, although necessary to compare alternative theoretical models (Anderson and Gerbing 1988), specification searches are not a reliable means to identify Type I and Type II errors. The results of specification searches can vary with sample size, sample distribution, or the means to test for differences across models (MacCallum 1986). As a result, while we encourage OM scholars to use specification searches as a means to test and develop theory, we recommend they evaluate the outcomes of such searches on the merits of their theoretical implications.

Further, it is important to note that while one can use SEM to estimate misspecified measurement models, doing so results in greater chances of Type I and Type II errors (MacCallum and Browne 1993). When exogenous constructs are misspecified, path estimates leading from misspecified formative constructs exhibit an upward bias and paths leading to misspecified formative constructs exhibit a downward bias (Jarvis *et al*. 2003). Follow-up studies confirmed these findings and identified conditions under which Type I and Type II errors are likely to occur due to errors in specifying causality (MacKenzie *et al*. 2005, Petter *et al*. 2007). Table 5 states the conditions under which errors occur if constructs are misspecified. In our empirical illustration, if we used covariance based SEM to model cooperation as a reflective dependent variable would make a Type I error more likely – suggesting that relationships automating interactions with IT was significant, when in fact the relationship is not.

5. Summary of guidelines for OM researchers

The objective of this article is not to critique OM research, but to provide constructive guidance on how to more tightly link SEM's use to OM theory. We present our summary of guidelines organised around the two major themes – structural model and measurement model.

5.1 *Structural model*

SEM may be used to build or test theory. When selecting an SEM technique, one should consider a theory's stage of development. In making decisions, OM researchers should consider the following issues:

(1) Exploratory techniques are well-suited for establishing the significance of a relationship and whether it explains a meaningful amount of variance in an endogenous construct. Because of the components based approach to estimating relationships, exploratory techniques such as PLS are less prone to Type I error and better-suited for small, non-normal data sets often collected for initial tests of relationships.
(2) Confirmatory techniques provide global tests of 'fit' of a well-specified theoretical model to the observed data. However, because alternative models may yield equivalent estimates of 'fit', it is important to specify nested as well as alternative theoretical models so that one may assess the performance of *a priori* models relative to alternative explanations for relationships in the data.
(3) Confirmatory techniques may be used to build theory derived from well-established sets of constructs. In doing so, one must consider multiple measures of 'fit' as well as whether respecified models offer theoretical insight into phenomena. Further, it is important to acknowledge when insight into relationships is gleaned from exploratory analysis. If one extends theory through testing alternative models, one must acknowledge the increasing probability of introducing unfounded relationships into theoretical models.

5.2 *Measurement model*

Regardless of whether the SEM technique is exploratory or confirmatory, it possesses the ability to integrate measurement and structural models. In evaluating whether a construct is formative or reflective, scholars must carefully consider the theoretical definitions of constructs and their implications for answering the questions presented in Table 3.

Based on an OM scholar's answers to these questions, practical issues may force one to use exploratory, components based SEM over more widely diffused confirmatory SEM techniques. The decision tree shown in Figure 8 notes issues to be considered as scholars select an analytic technique.

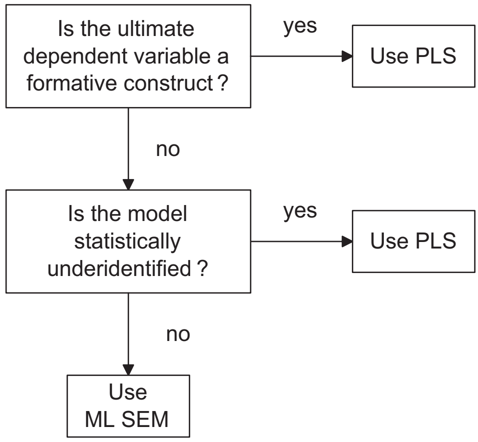

Figure 8. Decision tree for modelling formative constructs in PLS or ML SEM.

6. Conclusion

In this paper, we have presented a conceptual review of terms, key issues, and approaches to using SEM as well as an applied illustration of PLS of an underutilised approach to SEM. Our paper contributes to OM research in two ways. First, it provides a simple roadmap of issues that OM researchers should consider when they use SEM. While prior papers in OM and other business disciplines focus on assessing the 'state of the field' through counting the number of articles or type of measures in articles, the present study moves beyond simply counting papers to identify key issues that frame decisions related to SEM's application in OM research. In our review we underscore that decisions regarding theory (building or testing) and measurement (direction of causal agency) should guide the selection of SEM technique. By doing so, we hope to sensitise OM researchers to crucial decisions that shape the use and interpretation of SEM in empirical research. Second, consistent with our goal of fostering appropriate use of SEM, our study provides an applied illustration of components based SEM (e.g., PLS), explains how it differs from widely diffused covariance based SEM techniques, and provides clear guidelines for decisions related to selecting an SEM technique. In the OM field where addressing research questions requires theoretical and methodological excellence, we believe that adopting advances in SEM provides opportunities for building and testing theory. As familiarity with a wider range of applications of SEM grows, we hope that OM researchers will succinctly present technical matters and be more sensitive to the theoretical issues raised in this study.

Notes

1. Appendix 1 provides the details of our literature review methodology.
2. While it is important to appropriately conceptualise constructs as either formative or reflective, we would like to note that formative representations are fraught with problems like interpretational confounding and external consistency (Howell *et al.* 2007). Discussion of these issues is beyond the scope of this paper, but interested readers are referred to Howell *et al.* on the care needed for good formative representations.

3. Indicators of formative constructs may be referred to as cause, causal, composite, or formative indicators. We use the term formative indicators simply for consistency. For a detailed review of issues related to formative issues please see the *Journal of Business Research* volume 61, issue 12, special issue on formative indicators (2008).
4. PLS can be acquired from a variety of sources. VisualPLS is available at http://fs.mis.kuas.edu.tw/~fred/vpls/. SmartPLS is available at http://www.smartpls.de/forum/. PLSGraph can be purchased from Wynne Chin – wchin@uh.edu.

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Appendix 1. Literature review methodology

To evaluate the use of advanced SEM applications in OM research, we reviewed six widely regarded journals: *Decision Sciences* (DS), *International Journal of Operations and Production Management* (IJOPM), *International Journal of Production Research* (IJPR), *Journal of Operations Management* (JOM), *Management Science* (MS), and *Production and Operations Management* (POM). All issues of these journals between 1995 and 2007 were searched for empirical SEM applications (see Table 6).

One hundred and sixty-five papers satisfied our selection criteria, 96 per cent of which were published after 1999. The final sample of this study includes papers which reported any of the following: (1) confirmatory measurement models; (2) structural models with single indicators; and (3) integrated measurement/structural models. Papers using exploratory factor analysis, path analysis, and regression analysis were excluded from the sample.

Table 6. Number of SEM articles published by year and journal.

	DS	IJOPM	IJPR	JOM	MS	POM	Total
1995	0	0	0	0	2	0	2
1996	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0
1998	2	0	0	3	0	0	5
1999	2	0	0	6	0	1	9
2000	3	0	1	4	1	0	9
2001	1	0	3	5	1	3	13
2002	0	2	2	5	0	0	9
2003	0	1	1	7	0	4	13
2004	6	2	4	5	1	2	20
2005	1	7	4	3	0	0	15
2006	2	3	2	16	0	0	23
2007	1	5	7	25	4	5	47
Total	18	20	24	79	9	15	165
(%)	11	12	15	48	5	9	100

Appendix 2. Construct measures

Automating Interactions with Information Technology

Please indicate the extent to which these activities are carried out manually or executed automatically by the application of information technology:

(1) Exchanging information in components requirements, availability, price, etc.
(2) Ordering Components C.
(3) Shipping and receiving Components C.
(4) Inventory control (for Components C).
(5) Invoicing and payment for Components C.

Product Complexity

Please indicate the extent to which you agree or disagree with following statements as they pertain to the ordering of Components C by circling a number between 1 (strongly agree) and 7 (strongly disagree):

(1) Components C tend to be technically complex to describe.
(2) Components C require a lot of information to fully describe.
(3) Components C have a large number of sub-components to describe.
(4) Components C need significant engineering effort and expertise.
(5) Components C tend to be relatively sophisticated.

Cooperation

Please indicate the extent to which you believe that the following descriptions regarding your relationship with Supplier S are completely accurate (1) or completely inaccurate (7) (please circle the appropriate number):

Flexibility:

(1) Flexibility in response to requests for changes is a characteristic of this relationship.
(2) When some unexpected situation arises, the parties would rather work out a new deal than hold each other to the original terms.
(3) It is expected that the parties will be open to modifying their agreements if unexpected events occur.
(4) Changes in previously agreed prices are not ruled out by the parties, if considered necessary.

Information exchange:

(1) In this relationship, it is expected that any information that might help the other party will be provided to them.
(2) Exchange of information in this relationship takes place frequently and informally and not only according to a prespecified agreement.
(3) It is expected that the parties will provide proprietary information if it can help the other party.
(4) It is expected that the parties keep each other informed about events or changes that may affect the other party.

Extent of shared problem solving:

(1) In most aspects of this relationship the parties are jointly responsible for getting things done.
(2) Problems that arise in the course of this relationship are treated by the parties as joint rather than individual responsibilities.
(3) The parties in this relationship do not mind owing each other favors.
(4) The responsibility for making sure that the relationship works for both parties is shared jointly.

Restraint in the use of power:

(1) The parties feel it is important not to use any proprietary information to the other party's disadvantage.
(2) A characteristic of this relationship is that neither party is expected to make demands that might be damaging to the other.
(3) The parties expect the more powerful party to restrain the use of its power in attempting to get its way.