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Examining the Impact of Multicollinearity in Discovering Higher-Order Factor Models

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Abstract:

Theory-driven structural equation modeling (SEM) is an increasingly popular technique for analyzing quantitative data in Information Systems research. Since 1994, 20% of all papers in top-tier journals use structural equation modeling [Urbach and Ahlemann, 2010]. Higher-order factor structures have been widely discussed from a number of theoretical perspectives [e.g., Bagozzi and Edwards, 1998; Hayduk, Ratner, Johnson and Bottorff, 1995; Law, Wong and Mobley, 1998]. Our intention is not to contradict these theoretical discussions but to postulate that empirical analysis can assist in the discovery of emergent higher-order structures where perhaps not initially proposed. As constructs have become both more numerous and specific, the existence of higher levels of multicollinearity, even when discriminant validity is evident, are becoming problematic for assessing the role of individual constructs. Thus, there becomes a need for a higher-order structure to represent these relationships. In this paper, we present a six-step methodology for researchers who have structural models suffering from multicollinearity, positing that multicollinearity can obscure an underlying higher-order structure. We present findings from an empirical study where multicollinearity had masked the presence of a higher-order structure. We conclude with a proposed methodology for discovering higher-order factor models.

Keywords: Structural equation modeling (SEM), multicollinearity, higher-order factor model, second-order factors

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I. INTRODUCTION

Theory-based structural equation modeling (SEM) is an increasingly popular technique in Information Systems research. Since 1994, nearly 11% of all papers in MISQ and ISR used PLS, and 9% employed a covariance-based approaching, translating to 20% of all papers in top-tier journals using structural equation modeling [Urbach et al., 2010]. Multiple papers have emerged to provide guidance to researchers interested in testing a theory-based model using structural models. The same cannot be said, however, for discovering emergent higher-order factors within structural models in cases where structural models fail to overcome acceptable thresholds of fit or discriminant validity. We are not alone in our assessment of this concern. Evermann and Tate [2011] recently proposed a methodology for dealing with models that do not achieve desirable fit and then using these models as the basis for theory building. We concur with Evermann and Tate [2011] that "models that do not fit the observed data are useful, because, given the extensive theory building and data collection effort that goes into any research study, we can learn much from them" (page 633). However, rather than focusing on model fit (more broadly), we are instead focusing on how models that suffer from high levels of multicollinearity among constructs (e.g., a set of exogenous constructs) can be improved through the development of higher-order factor models representing these relationships among constructs.

While Evermann and Tate [2011] were broad in their focus, we focus our scope on researchers who have multicollinearity within their models. Specifically, what can researchers do when they follow the guidelines to assess their measurement model and pass tests of discriminant validity (within the acceptable boundaries), yet find that their structural model yields no significant relationships? Moreover, on further investigation, the researcher discovers that the first-order constructs suffer from multicollinearity. We posit that the researchers, in this case, lack sufficient guidance about how to test for an emergent higher-order structure within their data. Furthermore, while tutorials have discussed higher-order structures [Wright, Campbell, Thatcher and Roberts, 2012], their focus was on theory-driven models and not circumstances where researchers, on finding that the data does not support the model, can then use the structural model along with theory to test for a latent higher-order structure.

Within the measurement community, we have developed a robust set of approaches at the item level to assess whether or not items exhibit discriminant validity. Within their discussion on evaluating test validity, Campbell and Fiske [1959] introduced the MTMM (multitrait-multimethod) approach to assess discriminant validity among single item measures. This approach was extended to SEM [Bagozzi and Yi, 1993; Marsh and Hocevar, 1988; Millsap, 1990] and has been applied extensively across numerous disciplines. As SEM rose in popularity, the elements of construct validity were developed for multi-item constructs, with Fornell and Larcker [1981] developing a framework to assess construct validity. Discriminant validity is assessed by determining whether the variance accounted for in the observed items by the construct exceeds the variance in the items associated with other constructs. By examining item loadings on the hypothesized constructs (convergent validity) as well as loadings on other constructs (unidimensionality), researchers can make the necessary adjustments in their measurement models to ensure discriminant validity.

As researchers move to the construct level, a similar challenge remains: are there relationships among the constructs that can be represented by a hierarchical or higher-order structure? Just as we identified sets of observed measures and validated their consistency in representing a construct, are there "sets" of constructs that, when taken together, represent the dimensions of a "higher-order" latent construct? Since Marsh and Hocevar [1985] provided the first empirical application of SEM for identifying higher-order models, researchers have employed hierarchical structures to represent a wide array of effects (e.g., dimensionality, common method effects and common versus specific factors). As constructs have become both more numerous and more specific, the existence of higher levels of multicollinearity, even when discriminant validity is evident, are becoming problematic for assessing the role of individual constructs. Thus, a need exists for a higher-order structure to represent these relationships. Just as Evermann and Tate [2011] have argued that models with poor fit can be useful in theory generation, we similarly argue that models with high levels of multicollinearity among constructs can be used to build new theory. We posit that in models with multicollinearity there may exist a higher-order structure that can be used to account for the model employed by the researcher.

In this paper, we seek to provide a tutorial for researchers who find multicollinearity (despite having an "accepted" level of discriminant validity from an SEM perspective) at the latent construct level to explore whether their data has a higher-order structure. While not every dataset has a higher-order structure concealed in the data, we will explore how this structure can emerge by simultaneously exploring the data and theory. Although higher-order structures are not pervasive within our discipline, every extant study that presented a higher-order model justified it theoretically. This tutorial, however, presents a methodology that enables a researcher to employ data in combination with theory to test for the existence of an emergent higher-order structure.

II. MULTICOLLINEARITY AND HIGHER-ORDER CONSTRUCTS IN INFORMATION SYSTEMS RESEARCH

We begin our tutorial with an investigation of the use of higher-order constructs within the IS research stream. A higher-order construct is a single theoretical concept that is measured by several related constructs [Law et al., 1998]. In a recent tutorial, Wright et al. [2012] raised the issue of higher-order models and presented a tutorial that guided researchers on how to represent and model these structures within various statistical applications. This tutorial assumed that, at the lower order, each of the latent constructs exhibited discriminant validity. Discriminant validity, however, does not necessarily mean acceptable levels of multicollinearity among the first-order constructs. Thus, it is first important to understand the relationship between higher-order structural models and multicollinearity.

To explore the relationship between multicollinearity and higher-order structural models that have been accepted in the literature, we conducted a review over the past ten years for the journals of *MIS Quarterly* (MISQ), *Information Systems Research* (ISR), the *Journal of Management Information Systems* (JMIS), and the *Journal of the Association for Information Systems* (JAIS). Our objective was to identify articles that: (a) had created and (b) empirically tested a higher-order construct, and (c) reported a correlation matrix among constructs that enabled us to replicate the results. The objective was to highlight a representative sample of previous work and then examine the relationship between multicollinearity among the original constructs and the formation of second-order constructs. Table 1 lists the articles containing higher-order constructs satisfying our three criteria.

Table 1. Survey of Second-Order Constructs in IS Research

Citation	Second-Order Construct	First-Order Dimensions
Wright et al. [2012]	Cognitive absorption	• Temporal dissociation • Focused immersion • Heightened enjoyment • Control • Curiosity
Lu and Ramamurthy [2011]	IT capability	• IT infrastructure capability • IT business spanning capability • IT proactive stance
Tanriverdi [2005, 2006]	IT relatedness	• IT strategy making • IT vendor management • IT human resource management • IT infrastructure
Rai, Patnayakuni and Seth [2006]	IT infrastructure integration for SCM	• Data consistency • Cross-functional SCM application integration
	Supply chain process Integration	• Information flow integration • Physical flow integration • Financial flow integration
	Firm performance	• Operations excellence • Customer relationship • Revenue growth
Son and Kim [2008]	Perceived justice	• Interactional justice • Procedural justice • Distributive justice
Sun [2012]	Adaptive systems use (3rd order); Revising the content of FIU (2nd order); Revising the spirit of FIU (2nd order)	• Trying new features • Feature substituting • Feature combining • Feature repurposing
	Novel situations	• New tasks • Other people's use • Changes in system environment

Table 1. Survey of Second-Order Constructs in IS Research – Continued		
Teo, Wei and Benbasat [2003]	Mimetic pressures	• Extent of adoption among competitors • Perceived success of competitor adopters
	Coercive pressures	• Perceived dominance of supplier adopters • Perceived dominance of customer adopters • Conformity with parent corporation's practices
	Normative pressures	• Extent of adoption among suppliers • Extent of adoption among customers • Participation in industry, business, and trade associations
We identified other second-order constructs that failed to meet our three criteria, including Barki, Titah and Boffo [2007]; Dimoka, Hong and Pavlou [2012]; Gold, Malhotra and Segars [2001]; Gray, Parise and Iyer [2011]; Mithas, Jones and Mitchell [2008]; Ragu-Nathan, Tarafdar, Ragu-Nathan and Tu [2008]; and Zhu [2004]		

Using the correlation matrix among first-order constructs, we calculated the Variance Inflation Factor (VIF) for each of the constructs [Belsley, Kuh and Welsch, 2005; Hair, Black, Babin, Anderson and Tatham, 2006; Neter, Kutner, Nachtsheim and Wasserman, 1996; and Theil 1971). VIF is a measure of multicollinearity, with a higher number indicating a greater level of multicollinearity among the constructs. To examine the level of multicollinearity among higher-order structural models, we employed the following methodology (based on Hair et al. [2006]):

1. Using *only* the first-order constructs contained in the higher-order structure, an ordinary least squares regression was performed for each construct acting as the dependent variable and the other first-order constructs as independent variables. This process repeated until each of the first-order constructs had been specified as the dependent variable.

2. The VIF factor was then calculated for each construct, using the formula:

$$VIF = \frac{1}{1 - R(i)^2}$$

where R^2 is the coefficient of determination of the regression equation in step one.

3. Using a VIF of 5 or higher as an indicator of high multicollinearity [Menard 1995], each first-order construct can be assessed for its multicollinearity with other first-order constructs. Table 2 lists VIF's for each of the first-order constructs in the selected higher-order structures.

Table 2. VIF Calculations for Survey of Second-Order Constructs in IS Research

Author	Second-Order Construct	Dependent Variable Specified for Analysis	First-order Dimension	VIF
Wright et al. [2012]	Cognitive absorption	Intention	Temporal dissociation	1.672
			Focused immersion	1.531
			Heightened enjoyment	2.347
			Control	1.832
			Curiosity	1.598
Lu and Ramamurthy [2011]	IT capability	Market capitalizing agility	IT infrastructure capability	1.895
			IT business spanning capability	2.271
			IT proactive stance	2.089
Tanriverdi [2005, 2006]	IT relatedness	Past firm performance	IT strategy making	2.552
			IT vendor management	2.612
			IT human resource management	2.312
			IT infrastructure	2.188
Rai et al. [2006]	IT infrastructure integration for SCM	Operations excellence[1]	Data consistency	1.730
			Cross-functional SCM application integration	1.448
	Supply chain process integration		Information flow integration	1.781
			Physical flow integration	1.442
			Financial flow integration	1.104

Table 2. VIF Calculations for Survey of Second-Order Constructs in IS Research – Continued				
Son and Kim [2008]	Perceived justice	Refusal	Interactional justice	2.235
			Procedural justice	2.174
			Distributive justice	1.435
Sun [2012]	Novel situations	Trying new features[1]	New tasks	1.898
			Other people's use	2.384
			Changes in system environment	1.946
Teo et al. [2003]	Mimetic pressures	Adoption intention	Extent of adoption among competitors	4.016
			Perceived success of competitor adopters	2.056
	Coercive pressures		Perceived dominance of supplier adopters	2.181
			Perceived dominance of customer adopters	2.223
			Conformity with parent corporation's practices	1.039
	Normative pressures		Extent of adoption among suppliers	3.607
			Extent of adoption among customers	2.173
			Participation in industry, business, and trade associations	1.124

[1] Since the dependent variable was a second-order construct as well, we selected one of the dimensions of the second-order DV as the dependent variable for the analysis and focused only on the VIF for the independent variables

Our analysis reveals that higher-order structures are not always masked by the presence of multicollinearity. Does this negate the case for assessing multicollinearity and then looking to higher-order structures as a possible outcome? We believe not. In each of the cases that we identified from previous literature, the higher-order structures were theoretically argued and then empirically tested. In contrast, however, we posit the need to accommodate other motivations for the creation of higher-order structures. We propose that it is possible (and justifiable) that the presence of multicollinearity may actually be an indicator of the presence of a higher-order structure, and this multicollinearity (when paired with theoretical logic) can be an alternative motivation for the creation of these structures. Thus, while the presence of multicollinearity among the lower levels of the structure does not *always* indicate the presence of a higher-order structure, in certain cases, and with theoretical support, we posit that multicollinearity may indicate the presence of a higher-order structure. This tutorial provides guidance on how to determine whether a researcher's data that exhibits multicollinearity may merely be masking a higher-order structure.

We suggest that the gap in the literature regarding a methodology for arriving at an emergent higher-order structure has created the absence of previously published higher-order structures exhibiting high degrees of multicollinearity (or high VIF). Thus, as a result, researchers who find, on running statistical testing, that high multicollinearity exists in their data might not pursue publication of their work, attributing this outcome to fatal flaws of methodology, analysis, or data collection. We propose an alternative for researchers in this position: that it is possible that there are higher-order structures within these types of findings that can be identified by multicollinearity. By following the guidelines below, this tutorial provides direction about an alternative method for detecting a latent higher-order structure.

An even more common problem may be researchers who do not recognize the potentially high degree of multicollinearity among the constructs ("They all passed the discriminant validity tests, so we are fine") that may be adversely impacting their results. This problem is just as we see with high multicollinearity confounding interpretation in linear models. We further suggest that most researchers have at one time or another had to confront the presence of multicollinearity within their dataset, and they simply choose to not pursue publication. However, what are the origins of multicollinearity, and from where did it derive? To satisfy concerns over unidimensionality, researchers have increasingly developed sets of duplicative and redundant items for constructs in order to achieve desirable psychometric properties. While this generally achieves the goal of a well-fitting measurement model, it also reduces the explanatory power and theoretical usefulness of the construct [Gerbing, Hamilton and Freeman,1994]. At the construct level, another set of issues emerges. First, the creation of more specific constructs leads to a larger number of constructs to be accommodated. Furthermore, there is greater potential that these separate constructs are now really dimensions of a higher-order construct. Second, by overly narrowing down our constructs and increasing the number of constructs that may be dimensions of the higher-order construct, we have introduced the potential for higher degrees of multicollinearity. Thus, in our quest for increased specificity and well-grounded constructs, we narrow the domain/scope of the constructs and introduce multicollinearity, which would not be present with constructs representing broader content domains.

While a researcher might see the distinct nature of their constructs at the theoretical level, empirical distinctions, particularly in the early stages of construct development, may be much more difficult to discern. Even when discriminant validity can be established, the high levels of multicollinearity may create interpretational difficulties and even empirical issues when integrated into a structural model. We agree with Gerbing et al. [1994] that these types of first-order factors should be posited as the constituent facets of constructs of interest, or the “building blocks” of the second-order constructs. In this view, each construct acts as a facet defined by a more specific and unidimensional set of items, and the constructs/facets can then be treated as the indicators of second-order factors. Higher-order factor structures have been widely discussed from a number of theoretical perspectives [e.g., Bagozzi and Edwards, 1998; Hayduk et al., 1995; Law et al., 1998]. Our intention is not to contradict these theoretical discussions but rather to postulate that empirical analysis can assist in the discovery of theoretically consistent higher-order structures where perhaps not initially proposed.

Furthermore, for higher-order structures that exhibit multicollinearity, there are detrimental consequences that correspond to the high levels of VIF. Higher-order structures with multicollinearity will appear to suffer statistical consequences such as a failure to achieve discriminant validity (e.g., high correlations between the latent constructs), failure to overcome established guidelines for common method bias, low path loadings for relationships that should be significant, and low levels of fit of statistical models for models with theoretical support. We postulate that one explanation for these findings could be the presence of a latent higher-order structure. Moreover, if a structured methodology is followed to investigate the findings, we posit that researchers can conclude whether a higher-order structure is present and, if so, they can present a higher-order structure that is both empirically and theoretically justified. We believe that these results will contribute to our body of knowledge.

III. MULTICOLLINEARITY AND OTHER RELATED METHODOLOGICAL GUIDELINES

A broad segment of research within the IS community is focusing on methodological weaknesses within our field, highlighting concerns over the specifications of our structural models in general [e.g., Gefen et al., 2000], the use of formative versus reflective models [e.g., Petter et al., 2007 and Diamantopoulos, 2011], and how to conceptualize and model multi-dimensional constructs [Wright et al., 2012]. However, in each of these cases, the tutorials and approaches have focused mainly on the need for theory—arguing for strong theoretical justification for model specification, item measurement, and multi-dimensional construct conceptualization (respectively). We agree with the importance of strong theory and do not view our position as being opposed to or in contrast to this body of work. Instead, this tutorial is meant to assist researchers in recognizing and dealing with certain results that may indicate the presence of higher-order structures that are theoretically consistent but may not have been initially proposed. We therefore position our work as an extension of Wright et al. [2012], with our focus on multi-dimensional constructs in addition to Evermann and Tate [2011], which postulates that models with poor fit still have value to our field. Therefore, the presence of multicollinearity within an empirical study may indicate that there is a new way of conceptualizing a construct in a manner that was not previously identified.

IV. GUIDELINES FOR SPECIFYING EMERGENT HIGHER-ORDER STRUCTURES FROM MODELS CONTAINING MULTICOLLINEARITY

We will now outline a six-step methodology for researchers to follow to discover emergent higher-order structures. Our methodology begins with two basic assumptions: (1) that there is an a priori research model with theoretical support, and (2) that the research has resolved issues of model specification (using the work of Gefen et al., 2000), measurement (i.e., formative versus reflective, based upon Petter et al., 2007 and Diamantopoulos, 2011), and that there is appropriate specification of the higher-order constructs (if applicable, based upon Wright et al., 2012). In our approach, we seek to balance three main considerations: (1) the conceptual basis for the higher-order structure; (2) the empirical support for that structure; and (3) the practical concerns of the parsimoniousness of our models. With these assumptions and considerations in mind, our methodology begins.

Step 1: Test the A Priori Model

The first step in our methodology requires researchers to test the a priori structural model using the appropriate application (e.g., EQS, AMOS, LISREL, Smart PLS, etc.). Relying on accepted guidelines for SEM, researchers should examine the measurement and structural model to ascertain whether the model supports the theory. If the model converges within the acceptable limits of SEM testing, then there is no empirical (or theoretical) support for moving further through our steps. However, if the model does not fit the data within acceptable limits, then further diagnostics are necessary. We focus our attention on a particular diagnostic to deal with certain circumstances surrounding poor fit. Specifically, if researchers finds that there is multicollinearity among the constructs, then there is a possibility that there is a latent higher-order structure. This leads us to offer our first guideline:

Guideline 1: Researchers should satisfy issues related to model specification, the nature of the indicators, and the nature of the higher-order constructs and test the a priori research model prior to examining whether there is empirical and theoretical justification for the creation of novel higher-order structures.

Step 2: Isolate The Factors that Potentially Contain A Higher-Order Structure

Given a set of constructs with acceptable measurement construct properties, Step 2 identifies the factors that potentially contain a higher-order structure. In Step 1, we were running the entire structural model, so Step 2 is intended to examine the results from Step 1 to identify specifically a potential set of factors based on the analysis of the correlation among the constructs. These sets of constructs are most often found among the exogenous constructs, but they may also occur among endogenous constructs when mediating processes are specified by several constructs. This leads us to the following guideline:

Guideline 2a: Identify the potential factors that could be dimensions of a higher-order structure based on an analysis of the latent correlation matrix.

With this identification complete, the next step is to analyze the degree of multicollinearity. Following the three-step methodology discussed earlier for analyzing the VIF, researchers can then identify any constructs exhibiting multicollinearity above acceptable levels. As of the writing of this article, it is not possible to complete this step within traditional SEM software packages, so this requires researchers to import the correlation matrix of constructs (e.g., a PHI matrix in LISREL notation for exogenous constructs) into an alternative software package (e.g., SPSS or SAS) and calculate the VIF value for each of the identified factors. If the VIF value is not higher than the accepted guideline of 5.0 [Menard, 1995], then sufficient multicollinearity is not present, and additional reflection is necessary to determine whether a higher-order structure can be justified on other grounds. Note that the guideline of 5.0 for VIF is markedly higher than the 10.0 value often noted. In the case of higher-order structures, the threshold for justifiable higher-order structures is lower. For example, with the theoretical justification supporting the higher-order structures identified earlier (see Table 2), all of the constructs in those higher-order structures had VIF values below 5.0. So when first-order constructs do exhibit VIF values exceeding 5.0, they exhibit the potential for higher-order structures from an empirical perspective. This logic leads us to the following:

Guideline 2b: Using VF thresholds of 5.0, identify any potential constructs that may form higher-order structures.

Step 3: Rank Order the Inter-Construct Correlations

Step 3 is to take the set of potential factors with VIF values above 5.0 and rank order the inter-construct correlations from the highest to the lowest. The justification for this approach is that the inter-construct correlations that are the highest should be those that are closest theoretically. While the next step will be to ascertain if this is correct, the objective of this third step is to begin our understanding of the source of the multicollinearity. If the number of constructs becomes substantial, researchers may wish to employ more formalized techniques, including exploratory factor analysis or variable clustering approaches to assess the underlying structure [Roth and Roychoudhury,1991]. But in most cases, subjective judgment will suffice as a balance between empirical evidence and theoretical support. The guideline for Step 3 is as follows:

Guideline 3: Rank order the inter-construct correlations among the potential factors to identify those that are candidates for combination into a higher-order structure.

Step 4: Assess the Theoretical Meaning and Implementation of Each Construct

In the Step 4, we examine the combinations of constructs identified from Step 3 through the lens of theory. Using the specific survey items that were implemented and the construct definition, Step 4 focuses on combinations of constructs that could constitute a higher-order structure. In this step, a researcher is seeking to identify a series of alternative models that balances out our three considerations (theoretical, empirical, and practical). Theory constitutes a key step at this point because, even with strong empirical evidence, if these combinations of constructs cannot be theoretically justified, they should not be combined. This leads to our next guideline:

Guideline 4: By examining the theoretical similarities between constructs, create combinations of constructs that lead to higher-order structures (e.g., second- or third-order) and are theoretically justified.

Step 5: Combine Models of Exogenous Constructs into CFA Model

Once the combinations of constructs have been theoretically and empirically justified, Step 5 involves creating a model that focuses only on the discovered, higher-order structural model. Once the model is created, a confirmatory factor analysis (CFA) model should be run and the modification indices should be examined. The loadings of the first-order constructs on their higher-order constructs should also be examined to ensure that the items have significant loadings. The guideline for Step 5 is as follows:

Guideline 5: Combine the first-order constructs into an empirically and theoretically justified higher-order structural model to run a confirmatory factor analysis.

Step 6: Combine Models of Exogenous and Endogenous Constructs into a Full Structural Model

Assuming that an empirically and theoretically supported higher-order structure emerges from Step 5, Step 6 is to integrate the new higher-order emergent model into the full structural model that was initially tested in Step 1. If the a priori theoretical model is sound and complete, then multicollinearity should no longer be an issue. Our final guideline is as follows:

Guideline 6: Integrate the higher-order emergent structure into the a priori structural model and assess the full model using accepted SEM guidelines.

We have summarized our six steps in Table 3 below.

Table 3. Summary of Analysis Steps

Step		Reminders
1	Test a priori model.	This is a necessary test of the theory.
2	Isolate the factors that potentially contain a higher-order structure.	The presence of multicollinearity provides the motivation for the following steps.
3	Rank order the inter-construct correlations.	This provides an initial set of potential factors that can be used to create a higher-order structure.
4	Assess the theoretical meaning and implementation of each construct.	Focus on the theoretical meaning for each construct as well as the survey items used. Using theoretical logic as well as the inter-construct correlations, create a higher-order structure.
5	Combine models of exogenous constructs into CFA model.	Create a model focusing only on the discovered structural model. First, assess the modification indices to determine if these dropped significantly. Next, assess the loadings of the first-order constructs on their higher-order construct to ensure a significant loading.
6	Combine models of exogenous and endogenous constructs into a full structural model.	If the a priori theoretical model is sound and complete, then multicollinearity should no longer be an issue.

V. AN APPLICATION OF THE GUIDELINES FOR SPECIFYING EMERGENT HIGHER-ORDER STRUCTURES FROM MODELS CONTAINING MULTICOLLINEARITY

To demonstrate how these guidelines can be applied, we conducted an empirical study in the domain of IT outsourcing. Drawing from Expectation Disconfirmation Theory (EDT), a client-side model of expectation standards used by outsourcing providers was employed to assess the performance of a vendor [Schwarz, 2011]. While outside of the scope of this study, the theory claims that individuals judge the performance of an outsourcing vendor vis-à-vis expectation standards [Santos and Boote, 2003]. According to previous work, all nine of the expectation standards are orthogonal standards—that is, there is substantial discriminant validity between them. For the purpose of our work, we have selected eight expectation standards to serve as a demonstration of the role of multicollinearity in discovering higher-order factor models. For our nomological network, we will include all eight of these standards as independent variables and satisfaction with the vendor as the dependent variable. The proposed model is shown in Figure 1.

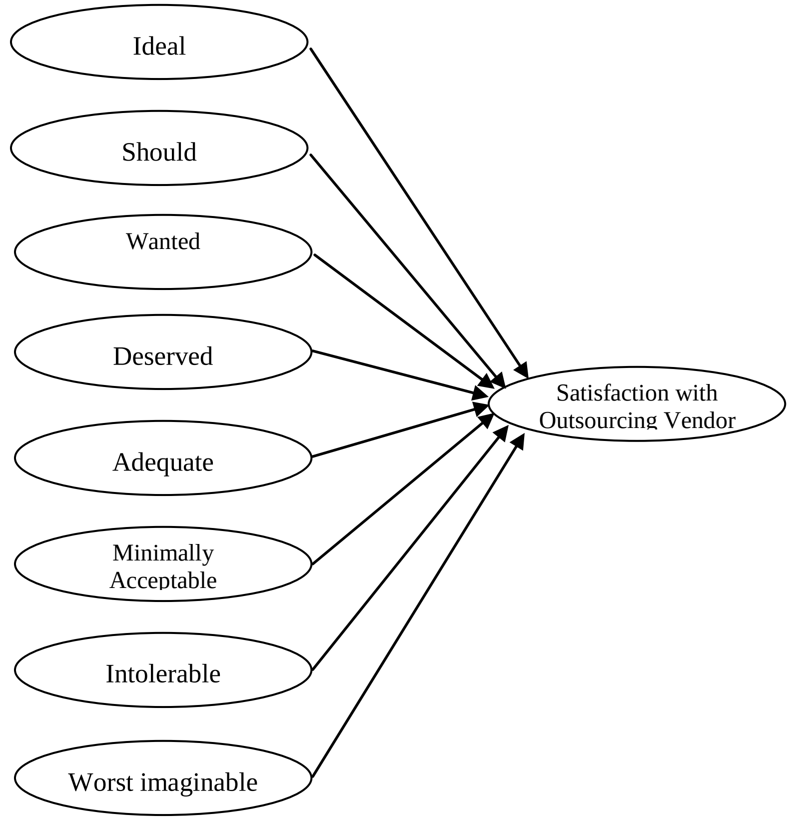

Figure 1. Proposed Model

Based on the conceptualization of the constructs, all of the constructs to be studied were defined and items were created. After conducting a literature review of the expectation standards, we identified eight standards used previously by researchers. Items were generated based on the definitions of each construct, formulating our items within the context of IT outsourcing. We have included the definitions of the constructs and the items in Table 4.

Table 4. Construct Definitions and Measurement Items

Three aspects of performance were asked for each expectation level:

1. The overall performance of my vendor was…
2. The extent to which the vendor met the needs of my organization was…
3. My overall experience with my vendor was…

All items with * were preceded with the following: All things considered...

We used a 7-point Likert scale (-3 to 3) to measure each expectation level.

Construct	Construct Definition	Preface	Anchors
Ideal	How well the vendor met the client's expectations of what they believe is ideal performance from their vendor regarding the overall outsourcing arrangement	Comparing my vendor's performance to what is the **ideal** level of performance…	Much worse than the ideal level…Much better than the ideal level
Wanted	How well the vendor met the client's expectations of what they wanted from their vendor regarding the overall outsourcing arrangement	Comparing my vendor's performance to what I **wanted** to receive from my vendor ….	Much worse than what I wanted to receive…Much better than what I wanted to receive

Table 4. Construct Definitions and Measurement Items – Continued			
Deserved	How well the vendor met the client's expectations of what they believed they deserved regarding the overall outsourcing arrangement	How would you compare your vendor's performance to what you **deserve** from your vendor according to industry practices…*	Much worse than I deserve… Much better than I deserve
Should	How well the vendor met the client's expectations of what they should receive regarding the overall outsourcing arrangement	How would you compare your vendor's performance on the following factors to what you **should** receive based on industry practices…*	Much worse than I should receive…Much better than I should receive
Adequate	How well the vendor met the client's expectations of what they believe is adequate performance from their vendor regarding the overall outsourcing arrangement	Comparing my vendor's performance to an **adequate** level of performance according to industry practices…	Much worse than what I should receive…Much better than what I should receive
Minimally Acceptable	How well the vendor met the client's expectations of what they believe is the minimum tolerable performance from their vendor regarding the overall outsourcing arrangement	How would you compare your vendor's performance to what is **minimally acceptable** according to industry practices…*	Much worse than is minimally acceptable…Much better than is minimally acceptable
Intolerable	How well the vendor met the client's expectations of what they believe is intolerable performance from their vendor regarding the overall outsourcing arrangement	Comparing my vendor's performance to what is **intolerable** according to industry practices…	Much worse than intolerable…Much better than intolerable
Worst Imaginable	How well the vendor met the client's expectations of what they believe is the worst imaginable performance from their vendor regarding the overall outsourcing arrangement	Comparing my vendor's performance to the **worst imaginable** level of performance from my vendor…	Much worse than the worst imaginable level of performance…Much better than the worst imaginable level of performance
Satisfaction with Outsourcing Vendor	The client's level of contentment with the vendor	Are you satisfied with your vendor?	Dissatisfied…Satisfied
		All things considered, I am ________ with my vendor.	Dissatisfied…Satisfied

After the survey was designed, a pilot study was conducted to ascertain the feasibility and improve the design of the research instrument. The measurement instrument was pre-tested using three individuals from the target sample in addition to three academics. The individuals were given the online survey and asked to provide feedback on the clarity and understandability of the instrument. Although most of the feedback was positive, modifications were made to certain questions based on feedback from the respondents in the pilot study. None of the responses from the pilot study were included in the final data set.

In order to test the proposed research model, a national survey was conducted to collect data for the study. To locate firms, a database of top IT executives, *The Directory of Top Computer Executives*, was employed as the basis for the sample. The directory has been used in prior publications [e.g., Ravichandran and Rai, 2000; and Schwarz, Jayatilaka, Hirschheim and Goles, 2009] and hence constitutes a reliable source for the sample. As we were seeking a particular target population, specifically the principal IT outsourcing decision maker, a survey respondent pool of potentially qualified subjects was created from the database. Since some of the IT executives in the database would "not possess the attribute(s) necessary" [Dillman, 1978, p. 42] to complete the survey (e.g., they do not engage in outsourcing or would not be considered the principal decision maker), a pre-qualifying stage involved sending an opt-in message to each of the e-mail addresses listed in the database, which enabled only key IT outsourcing decision makers to opt in and mitigated any unwanted messages [Mehta and Sivadas, 1995; Sheehan, 2001; Yun and Trumbo, 2000) to recipients not in the target population.

Using the methodology proposed by Dillman [1978; 2007], we employed the following steps. First, all of the IT executives in the database were sent a personalized pre-notification e-mail, offering the recipient an opportunity to opt in to the survey respondent pool if they qualify as part of the target population. Respondents indicated their interest in participating by opting in or responding to the e-mail. They were then sent an e-mail with an embedded link that directed them to the web-based survey. One hundred fifty-seven respondents qualified for the study and opted in to the survey respondent pool.

A total of 106 usable responses were received, for a response rate of 68%. This response rate is higher than the average response rate of 48.8% found in Yu and Cooper's [1983] meta-analysis of response rates and much higher than those obtained in many IS surveys on outsourcing [e.g., Mani, Barua and Whinston, 2010].

VI. THE PROPOSED METHODOLOGY FOR IDENTIFYING HIGHER-ORDER STRUCTURES

In presenting the results, we will structure our findings within a six-step methodology representing our prescriptive approach for researchers suffering with models exhibiting high multicollinearity. This illustrative model will be used as our exemplar for both diagnostics and future applications. First, we begin with a full test of our a priori research model.

Step 1: Test A Priori Model

Using the research model in Figure 1, we ran the proposed structural model using Amos 19.0 (build 1376). The first analysis involved assessing the psychometric properties of the eight constructs. We examined convergent validity, determined by evaluating the individual item reliabilities as represented by the loadings to their respective construct (Table 5) as well as convergent validity, assessed by the lack of significant cross-loadings on other constructs. All of the items were acceptable at over 0.90.

Table 5. Loading of Items

Item	Weight	Item	Weight
Adequate		Minimally Acceptable	
ADQ1	.988	OMN1	.967
ADQ2	.970	OMN2	.974
ADQ3	.976	OMN3	.985
Ideal		Should	
IDE1	.985	OSH1	.986
IDE2	.977	OSH2	.963
IDE3	.987	OSH3	.970
Intolerable		Wanted	
INT1	.978	WNT1	.960
INT2	.958	WNT2	.969
INT3	.994	WNT3	.971
Deserved		Worst Imaginable	
ODS1	.982	WRS1	.973
ODS2	.974	WRS2	.983
ODS3	.974	WRS3	.989

While the first analysis demonstrated that the items loaded appropriately on their respective construct, this does not indicate the reliability of the items. Using the loadings from the constructs, Cronbach's alpha was calculated for each of the constructs (Table 6). All of the items' constructs displayed reliability over 0.97.

Table 6. Cronbach's Alpha

Construct	Alpha
Adequate	0.985
Ideal	0.988
Intolerable	0.985
Deserved	0.984
Minimally Acceptable	0.983
Should	0.981
Wanted	0.977
Worst Imaginable	0.987

The final assessment of the measurement model involved calculating discriminant validity between the constructs.

While the correlations among constructs were in many cases quite high (to be discussed in more detail in the next section), the loadings of items within each construct supported discriminant validity between all constructs [Fornell and Larcker, 1981]. Specifically, to evaluate discriminant validity, we examined the correlations between the dimensions as well as the items. As the square root of the AVE exceeded the correlation between each dimension for all of the other dimensions, we concluded that we had established discriminant validity at the construct level.

Our analysis then proceeded with an examination of the structural model, specifically the path loadings for our theoretically supported research model (Table 7). The fit statistics also revealed some concerns: CMIN was 557.03 with 263 degrees of freedom, for a x2/df of 2.118. Our CFI was 0.952, with RMSEA equaling 0.103.

Table 7. Path Estimates for Proposed Research Model

	Path Estimate	S.E.	C.R.	P	VIF
Ideal	0.088	0.123	0.712	0.477	7.105
Should	0.424	0.148	2.866	0.004	8.993
Wanted	0.163	0.163	0.998	0.318	10.524
Deserved	-0.116	0.18	-0.644	0.52	11.779
Adequate	-0.122	0.099	-1.231	0.218	4.229
Minimally Acceptable	0.395	0.111	3.545	***	6.888
Worse Imaginable	0.09	0.111	0.807	0.42	3.669
Intolerable	0.18	0.113	1.585	0.113	5.506

From a theoretical perspective, particularly troubling in the proposed model was the finding that only two of the eight constructs demonstrated significant associations with satisfaction. These results would indicate, if only this model was examined, that a substantial number of the constructs display no relationship with the outcome. However, this finding conflicts with the substantial extant research that examined these expectation standards separately. Therefore, the next step was to determine whether a higher-order structure could be identified that provided a more theoretically supported perspective on these relationships.

Step 2: Isolate the Constructs that Potentially Represent a Higher-Order Structure

We next created the a confirmatory factor analysis (CFA) of our eight constructs (expectation standards) without the dependent variable, examining the correlations between constructs (Table 8). As noted earlier, high inter-constructs correlations (i.e., three over .9, even though they passed tests of discriminant validity) indicated that multicollinearity was a significant problem in the proposed model [Hair et al., 2006; Kline, 2005].

Table 8. Inter-Construct Correlations

Construct Relationship			Correlation	Construct Relationship			Correlation
Ideal	↔	Should	.854	Should	↔	Min_Acp	.849
Should	↔	Wanted	.891	Should	↔	Intolerable	.732
Deserved	↔	Adequate	.838	Should	↔	Worse_Imag	.618
Min_Acp	↔	Adequate	.809	Wanted	↔	Deserved	.906
Min_Acp	↔	Intolerable	.848	Wanted	↔	Adequate	.832
Worse_Imag	↔	Intolerable	.831	Wanted	↔	Min_Acp	.829
Ideal	↔	Wanted	.914	Wanted	↔	Intolerable	.706
Ideal	↔	Deserved	.877	Wanted	↔	Worse_Imag	.547
Ideal	↔	Adequate	.763	Min_Acp	↔	Deserved	.856
Ideal	↔	Min_Acp	.759	Deserved	↔	Intolerable	.728
Ideal	↔	Intolerable	.624	Deserved	↔	Worse_Imag	.627
Ideal	↔	Worse_Imag	.466	Adequate	↔	Intolerable	.734
Should	↔	Deserved	.932	Adequate	↔	Worse_Imag	.629
Should	↔	Adequate	.793	Min_Acp	↔	Worse_Imag	.741

After calculating the VIF values, each of the constructs (with the exception of *Worst Imaginable* and *Adequate*) exceeded the threshold of 5. Nonetheless, while there were two constructs that fell below the threshold, given the theoretical ties between this set of constructs, all of these constructs were moved on to the next analysis. [1]

Step 3: Rank Order the Inter-Construct Correlations

We then rank ordered the correlations among the constructs. This provided us with a potential for a baseline higher-order structure. In our case, the top two were: *Should* and *Deserved* (0.932) and *Ideal* and *Wanted* (0.914). This provided us with an initial structure, which could then be expanded based on additional empirical and theoretical support:

- *Should* and *Deserved* reflect a higher-order structure
- *Ideal* and *Wanted* reflect a higher-order structure

This initial finding led us to Step 4.

Step 4: Assess the Theoretical Meaning and Implementation of Each Construct

We then returned to our definitions of each construct, along with the survey items used, and assessed the theoretical logic for both the standards and the potential relationships with other standards as well as the items reflecting each construct. We discovered that the empirical considerations support the theoretical explanation for the underlying factor structure. By alternating between the theoretical and the empirical, we created a higher-order structure for our research model (termed our revised research model), displayed in Figure 2.

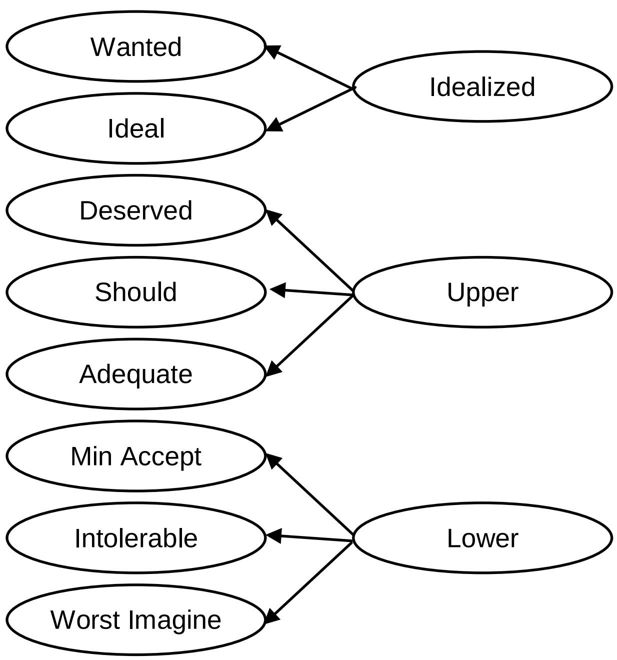

Figure 2. Revised Research Model

Step 5: Combine Models of Exogenous Constructs into CFA Model

We then re-ran our model as a CFA and examined the modification indices. Table 10 summarizes the correlations from our initial research model and the resulting modification indices once we introduced a higher-order structure. The modification indices represent the "unexplained" relationships among the constructs once the higher-order structure was implemented. As we can see, using the rule of thumb of modification indices above 4.0 being potentially significant, only three construct pairs exceeded this threshold, and two were quite close to 4.0. Only the construct pair *Worst Imaginable/Intolerable* exhibited a modification index (24.5) that would indicate any remaining unexplained relationship. This finding demonstrates the ability of the higher-order structure to represent effectively all of the relationships among constructs manifested in the high levels of multicollinearity in the higher-order

[1] The path loadings are included to demonstrate how the presence of multicollinearity turns path loadings insignificant

structure, which offers a much richer theoretical perspective. It should also be noted that the CFA model fit of both the initial proposed model and the higher-order model were quite comparable, thus rendering the higher-order structure a viable substitute for the original model.

Table 10. Discriminant Validity Following Model Respecification

Construct Relationship			Initial Research Model Correlations	Revised Research Model Modification Indices[2]
Ideal	↔	Should	0.854	0.109
Should	↔	Wanted	0.891	0.167
Deserved	↔	Adequate	0.838	0.057
Min_Acp	↔	Adequate	0.809	0.019
Min_Acp	↔	Intolerable	0.848	1.321
Worse_Imag	↔	Intolerable	0.831	24.5
Ideal	↔	Wanted	0.914	0.000
Ideal	↔	Deserved	0.877	1.581
Ideal	↔	Adequate	0.763	0.854
Ideal	↔	Min_Acp	0.759	0.21
Ideal	↔	Intolerable	0.624	1.266
Ideal	↔	Worse_Imag	0.466	4.163
Should	↔	Deserved	0.932	1.758
Should	↔	Adequate	0.793	4.877
Should	↔	Min_Acp	0.849	0.087
Should	↔	Intolerable	0.732	0.115
Should	↔	Worse_Imag	0.618	0.021
Wanted	↔	Deserved	0.906	1.968
Wanted	↔	Adequate	0.832	2.791
Wanted	↔	Min_Acp	0.829	1.334
Wanted	↔	Intolerable	0.706	0.62
Wanted	↔	Worse_Imag	0.547	0.772
Min_Acp	↔	Deserved	0.856	0.038
Deserved	↔	Intolerable	0.728	2.87
Deserved	↔	Worse_Imag	0.627	0.011
Adequate	↔	Intolerable	0.734	2.237
Adequate	↔	Worse_Imag	0.629	1.437
Min_Acp	↔	Worse_Imag	0.741	3.941

We should also note that the higher-order structure was a much more effective representation of the original eight constructs than was any reduction in the number of constructs. One remedy often employed to deal with high multicollinearity is to combine the constructs that are highly correlated. This approach would certainly seem reasonable for those construct pairs with high levels of correlations. However, competing models where these constructs pairs were joined displayed extremely high and significant changes in chi-square. For example, combining the constructs *Ideal* and *Desired* constituted the higher-order factor *Idealized*, resulting in a chi-square change of 145 with 7 degrees of freedom.

Step 6: Combine Models of Exogenous and Endogenous Constructs into a Full Structural Model

The last step in our analysis is to replace the original eight constructs with the higher-order structure in a structural model. As displayed in Figure 3, the results provide a higher-order structure, with all of the higher-order constructs having significant paths to satisfaction. Moreover, relationships among the original set of standards are not all explicitly represented in the model as path estimates upon satisfaction, but rather as correlations among the exogenous constructs. This allows for a more realistic calculation of indirect effects of the expectation standards on satisfaction versus the original proposed model.

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[2] The modification index in this application would correspond to the "cross loadings" in an EFA and be an indication of the unidimensionality. So within a second-order construct, these would be a measure of the extent to which the common variance of the first-order constructs was captured by the second order. When you look across second-order constructs, then the MI becomes the "cross loading" on the other second-order factor, which should be small. If we are applying the same criteria that we do for first-order constructs and its indicators, then these cross loadings should be non-significant to support unidimensionality of the second-order construct.

While our fit statistics still did not achieve a high degree of fit (CMIN of 940.58; df of 288; x2/df of 3.266; CFI of 0.894; and RMSEA of 0.147), this suggests that additional refinement of our model could be undertaken now that the issue of multicollinearity has been resolved. Generally speaking, when higher-order structures are created, fit does decrease; however, the equivalence of the r^2 between the models indicates that this approach has created a more parsimonious representation and identification of the underlying associations, both among the constructs and between the higher-order structures and the outcome. Nonetheless, in the case of our study, we repeated this approach an additional time and isolated an instance of a third-order construct that, when created, was able to be theoretically rich and provided fit statistics that fell within acceptable boundaries. This tutorial thus highlights how the application of our approach can yield rich theoretical insights.

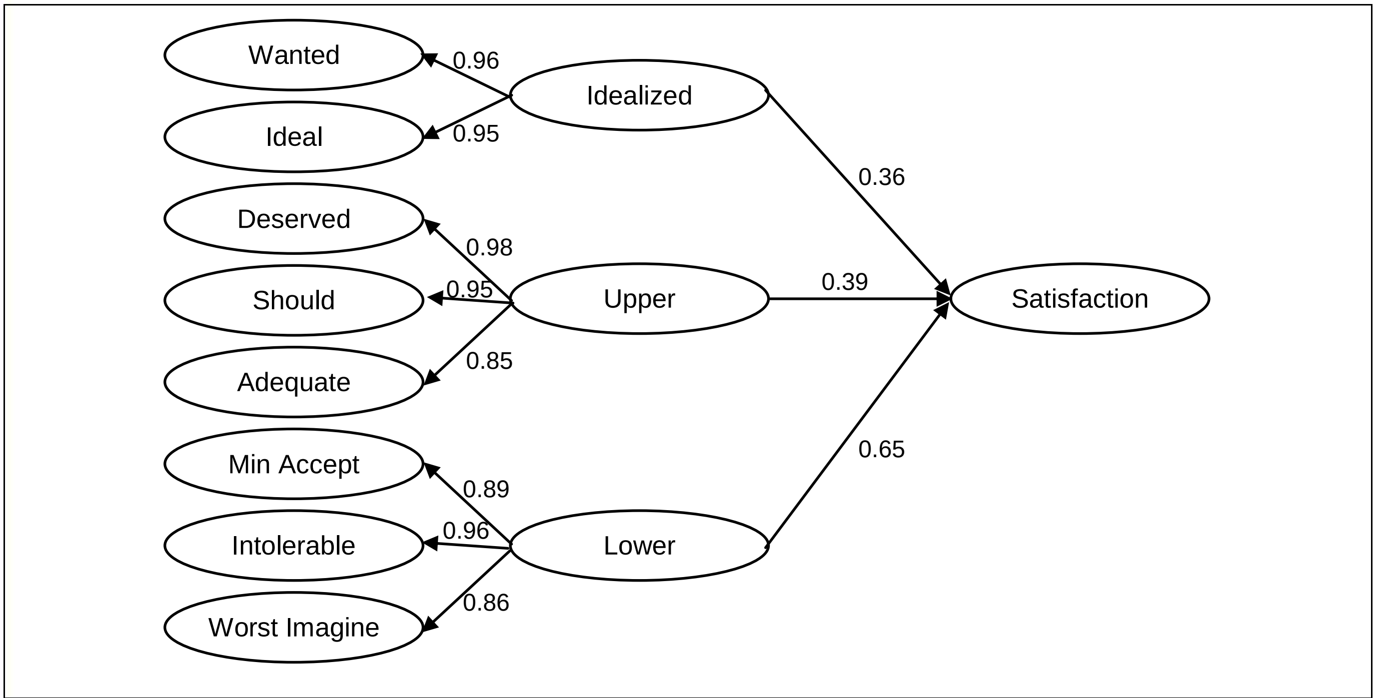

Figure 3. Higher-Order Model

V. CONCLUSIONS

In this paper, we presented guidelines regarding how to test for latent theoretically consistent higher-order structures and how to use the data collected for theory building. In summary, we have used the six steps outlined in Table 11.

Table 11. Summary of Analysis Steps

Step		Notes
1	Test a priori model	This is a necessary test of the theory.
2	Isolate the factors that potentially contain a higher-order structure	The presence of multicollinearity provides the motivation for the following steps.
3	Rank order the inter-construct correlations	This provides an initial set of potential factors that can be used to create a higher-order structure.
4	Assess the theoretical meaning and implementation of each construct	Focus on the theoretical meaning for each construct as well as the survey items used. Using theoretical logic as well as the inter-construct correlations, create a higher-order structure.
5	Combine models of exogenous constructs into CFA model	Create a model focusing only on the discovered structural model. First, assess the modification indices to determine if these dropped significantly. Next, assess the loadings of the first-order constructs on their higher-order construct to ensure a significant loading.
6	Combine models of exogenous and endogenous constructs into a full structural model	If the a priori theoretical model is sound and complete, then multicollinearity should no longer be an issue.

To our knowledge, this represents the first attempt to investigate how multicollinearity can be viewed as a mechanism to drive theory and revise our models. While we have demonstrated how first-order constructs can be abstracted to second-order constructs, we further propose that this methodology can be employed to further abstract second- to third-order constructs. We urge our colleagues to use this method to develop new models that include higher-order abstractions. Our work, however, does not come without limitations. First, our sample size decreases the statistical power of our models. However, the strength of the results suggests that the methodology can be employed by researchers effectively, even with small sample sizes. Next, we have employed a covariance-based approach. However, we postulate that the same methodology can be used within a PLS environment. Third, our work may suffer from common method bias. We propose that additional work be conducted to investigate the potential role of common method bias in assessing higher-order structures. Despite these limitations, however, we urge others to employ this methodology to contribute to the body of knowledge by testing for the existence of latent higher-order structures. Given the prevalence of SEM in the IS literature, we recommend that the next step involve employing new methods for theory-driven models. We believe that this approach is an important first step.

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Editor's Note: The following reference list contains hyperlinks to World Wide Web pages. Readers who have the ability to access the Web directly from their word processor or are reading the paper on the Web can gain direct access to these linked references. Readers are warned, however, that:

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