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# Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations

**Ned Kock**
Texas A&M International University
nedkock@tamiu.edu

**Gary S. Lynn**
Stevens Institute of Technology
glynn@stevens.edu

## Abstract

*Variance-based structural equation modeling is extensively used in information systems research, and many related findings may have been distorted by hidden collinearity. This is a problem that may extend to multivariate analyses, in general, in the field of information systems as well as in many other fields. In multivariate analyses, collinearity is usually assessed as a predictor-predictor relationship phenomenon, where two or more predictors are checked for redundancy. This type of assessment addresses vertical, or "classic", collinearity. However, another type of collinearity may also exist, here called "lateral" collinearity. It refers to predictor-criterion collinearity. Lateral collinearity problems are exemplified based on an illustrative variance-based structural equation modeling analysis. The analysis employs WarpPLS 2.0, with the results double-checked with other statistical analysis software tools. It is shown that standard validity and reliability tests do not properly capture lateral collinearity. A new approach for the assessment of both vertical and lateral collinearity in variance-based structural equation modeling is proposed and demonstrated in the context of the illustrative analysis.*

***Keywords***: *Collinearity, Vertical Collinearity, Lateral Collinearity, Multiple Regression, Structural Equation Modeling, Partial Least Squares, Electronic Communication.*

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# Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations

## 1. Introduction

The concepts of collinearity and correlation are often confused, even though they are distinct concepts (Hair, Black, Babin, & Anderson, 2009; Hamilton, 1987). Collinearity is a multivariate notion, whereas correlation refers to a pair of variables. Two or more variables are said to be collinear when they measure the same attribute of an object; the latter is also called a construct. In this sense, the variables “satisfaction with a technology” and “excitement about the technology” may be collinear, if the question-statements related to these two variables are seen as referring to the same object attribute “affective response to the technology” by the respondents of a questionnaire. Two variables are said to be correlated if they vary in concert with each other, even though the variables may measure totally different object attributes; for example, a person’s weight from 1 to 20 years of age, and the price of gasoline during those years.

Collinearity is usually assessed in models with multiple variables as a possible predictor-predictor redundancy phenomenon. This is what is referred to here as vertical, or “classic”, collinearity. Another type of collinearity may also exist, called here “lateral” collinearity. It refers to predictor-criterion collinearity. Unlike vertical collinearity, lateral collinearity is almost never explicitly tested for in multivariate analyses. (For reference, these and other key terms are listed in alphabetical order, with their respective definitions, in Appendix A.)

Lateral collinearity typically occurs when two variables that are hypothesized to be causally related measure the same construct. In a causal model, the two variables would be shown as linked by an arrow, with one pointing at the other. Lateral collinearity can lead to misleading results in a “stealth” way, because it can be masked by the appearance of a strong causal effect in the model. Strong causal effects are usually what researchers are interested in finding, since they provide decisive support for the researchers’ hypotheses.

We present an extended discussion of vertical and lateral collinearity and follow it with an illustration based on a variance-based structural equation modeling (SEM) analysis of data related to electronic communication in innovation teams. We use the analysis to exemplify collinearity, and do not present it as a standalone empirical contribution. By focusing on variance-based SEM, our illustration addresses the vast majority of univariate and multivariate data analysis techniques used in behavioral studies, which are conceptually special cases of SEM.

Variance-based SEM is a method to which pioneering information systems researchers contributed extensively (Chin, 1998; Chin, Marcolin, & Newsted, 2003), and which is used extensively in the field of information systems. Variance-based SEM is still methodologically underdeveloped when compared with covariance-based SEM (Haenlein & Kaplan, 2004; Hair et al., 2009; Schumacker & Lomax, 2004), even though it offers some distinct advantages that make it attractive to researchers in various fields (Chin, 1998; Chin & Todd, 1995; Fornell & Bookstein, 1982; Haenlein & Kaplan, 2004; Sun & Zhang, 2006).

We show that lateral collinearity can lead to misleading results and that this type of collinearity may occur “below the radar screen” as far as widely used validity and reliability tests are concerned. That is, standard validity and reliability tests do not properly capture lateral collinearity. We propose and demonstrate a new approach for the assessment of both vertical and lateral collinearity in the context of the illustrative analysis. The new approach allows for the concurrent assessment of vertical and lateral collinearity.

## 2. Relevance for Information Systems

We conducted a review of articles published between 2001 and 2011 in the following refereed journals: *Information Systems Research* (*ISR*), *Journal of the Association for Information Systems* (*JAIS*), and *MIS Quarterly* (*MISQ*). We conducted tests of collinearity in the context of empirical quantitative studies in 17 out of 361 articles in *ISR*, 7 out of 331 articles in *JAIS*, and 8 out of 385 articles in *MISQ*. None of those tests addressed lateral collinearity.

This situation is problematic because lateral collinearity may exist even when correlations among variables in multivariate analyses are relatively low (see discussion on correlation versus collinearity in Appendix B). Correlations must exist among variables for associations suggestive of causal relationships to be discovered. Notably, these correlations must occur in "lateral" relationships, which are the types of relationships that refer to hypothesized causal links. However, not only is collinearity different from correlation, but also collinearity cannot be reliably inferred from correlation values alone except for very simple models.

The likely negative impact of hidden lateral collinearity on theory development is particularly problematic, because it would allow researchers to find strong but artificial support for hypothesized causal relationships. That is, mistakes would be made in connection with the causal relationships themselves, as opposed to arguably more benign mistakes in the identification of redundancies among hypothesized predictors in causal relationships stemming from hidden vertical collinearity. Causal relationships are the epistemological essence of many theoretical models (Audi, 2003; Popper, 1992), which are frequently defined by those relationships (Bagozzi, 1980; Davis, 1985; Maruyama, 1998).

This paper's relevance for the field of information systems stems not only from the absence of lateral collinearity tests in published research in the field, but also from its contribution to solidifying the position of information systems as a reference field (Baskerville & Myers, 2002; Grover, Gokhale, Lim, Coffey, & Ayyagari, 2006). This paper contributes to solidifying the position of information systems as a reference field by addressing methodological issues that, while demonstrably relevant to the field of information systems, are also likely to be relevant to many other fields. This includes fields within and outside business, and extends to most fields employing multivariate data analysis methods.

## 3. Covariance- and Variance-Based SEM

Most basic and intermediate statistical tests used in behavioral studies can be shown to be special cases of multiple regression analysis. Those basic statistical tests include t tests, bivariate (a.k.a. univariate) correlation analyses, ANOVA, ANCOVA, MANOVA, and MANCOVA (Hair et al., 2009; Rosenthal & Rosnow, 1991). Multiple regression analysis can, in turn, be seen as a special case of path analysis, as path models are made up of interconnected blocks of variables with one or more predictor variables pointing at a single criterion variable. SEM is essentially path analysis with latent variables (Chin, 1998; Chin & Todd, 1995; Schumacker & Lomax, 2004), whereas each variable in a path model is measured through multiple indicators (e.g., multiple questions referring to the same construct in a questionnaire).

Therefore, all of the aforementioned statistical tests, including multiple regression and path analyses, can be seen as special cases of SEM (Kline, 1998; Maruyama, 1998; Mueller, 1996). In SEM latent variables are used in models instead of directly measured variables, which are (the latter) often referred to as indicators. Latent variables are obtained through iterative algorithms with specific criteria for convergence (Jöreskog & Wold, 1982; Schumacker & Lomax, 2004).

Latent variables are used in SEM to both minimize measurement error and collinearity; they also allow for instrument validity and reliability assessments (Gefen & Straub, 2005; Gefen, Straub, & Boudreau, 2000; Mueller, 1996; Schumacker & Lomax, 2004). These essentially allow researchers to check whether the results of SEM analyses can be trusted.

SEM techniques are usually divided into two main groups, covariance-based and variance-based (Chin, 1998; Fornell & Larcker, 1981; Schumacker & Lomax, 2004). They are also frequently referred to by other names, notably maximum likelihood and PLS-based SEM, respectively (Fornell & Bookstein, 1982; Jöreskog & Wold, 1982; Kline, 1998). The acronym "PLS" stands for either "partial least squares" or "projection to latent structures"; the first form is the most common, even though the second form was the originally intended form by Herman Wold, who is widely regarded as the creator of the technique (Adelman & Lohmoller, 1994; Jőreskog & Wold, 1982; Wold, Trygg, Berglund, & Antti, 2001).

It is generally and incorrectly believed that the calculation of latent variable scores in variance-based SEM eliminates collinearity among latent variables. Variance-based SEM has, indeed, been shown to be particularly effective at minimizing collinearity among latent variables (Chin et al., 2003; Haenlein & Kaplan, 2004), but collinearity may still remain if different latent variables are redundant (Temme, Kreis, & Hildebrandt, 2006), even when the measurement instrument passes general validity and reliability tests.

The work of various researchers, especially Karl Gustav Jöreskog, established covariance-based SEM as the most widely used method for SEM (Haenlein & Kaplan, 2004; Hair et al., 2009; Schumacker & Lomax, 2004). Variance-based SEM is a very different method (see, e.g., Haenlein & Kaplan, 2004; McDonald, 1996) and is still relatively underdeveloped. Much of its current development has been due to the pioneering work of researchers in the field of information systems, mostly notably Wynne Chin (Chin, 1998; Chin et al., 2003).

The underdevelopment of variance-based SEM hampers its broad utilization even though variance-based SEM can be complementary to covariance-based SEM (Chin, 1998; Haenlein & Kaplan, 2004; Sun & Zhang, 2006), estimating coefficients with similar interpretations but with different underlying algorithms (Chin & Todd, 1995; Fornell & Bookstein, 1982; Goodhue, Lewis, & Thompson, 2006; Marcoulides & Saunders, 2009; Marcoulides, Chin, & Saunders, 2009). While there are techniques by which collinearity may be indirectly or directly assessed in covariance-based SEM, such as the common method factor technique (Lindell & Whitney, 2001), this is not yet the case with variance-based SEM.

## 4. Vertical Collinearity

Two or more variables are said to be collinear if they measure the same underlying attribute of a tangible or intangible object (Echambadi & Hess, 2007; Miller & Wichern, 1977). In survey research, manifest variables are often measured based on answers to questions on Likert-type scales (Ju, Chen, Sun, & Wu, 2006; Schumacker & Lomax, 2004). The questions are meant to refer to similar mental representations in the researcher's mind (usually the designer of the questionnaire), as well as in the respondents' minds, and to cluster around latent variables. Latent variables are differentiated from manifest variables by not being measured directly. Both manifest variables and latent variables may present collinearity.

Latent variables reflect constructs. For the purposes of the discussion presented here, a construct is defined as a mental representation of an attribute of an object (Audi, 2003; Popper, 1992). The nature of a construct may vary across different individuals. For example, a researcher designing a questionnaire may have one mental representation of an attribute of an object, such as ease of use (attribute) of a particular information technology (object), but the respondents of the questionnaire may have a different mental representation.

Variables may be strongly correlated and yet have a low degree of collinearity (Hamilton, 1987). Yet, collinearity is often conflated with correlation (Douglass, Clader, Christy, & Michaels, 2003; Graham, 2003), since the presence of correlation is a necessary but not sufficient condition to characterize collinearity. Moreover, the relationship between correlation and collinearity, as generally measured, is nonlinear (see Appendix B).

Vertical collinearity is a "classic" type of collinearity in that it is traditionally assessed in multiple regression analyses (Echambadi & Hess, 2007; Hair et al., 2009). Multiple regression analyses estimate coefficients of association between multiple predictor variables (a.k.a. independent variables) and one criterion variable (a.k.a. dependent variable). In this context, vertical collinearity refers to predictor-predictor collinearity (Graham, 2003; Sengupta & Bhimasankaram, 1997).

Figure 1 illustrates the target of a vertical, or "classic", collinearity test in a block with $n$ predictor latent variables $LVp_1$, $LVp_2$, $LVp_3 \ldots LVp_n$ pointing at one criterion latent variable $LVc$. Any model used in variance-based SEM analyses can be decomposed into multiple blocks like this.

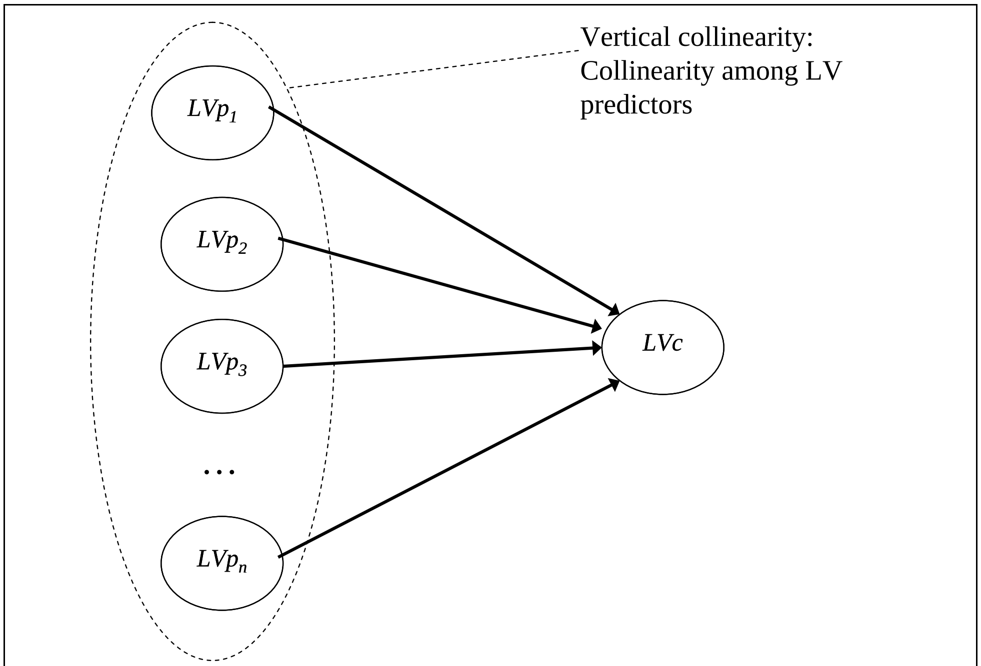



**Figure 1. Vertical, or "Classic", Collinearity**

There is a vast literature on vertical collinearity, dating back more than 30 years (Mosteller & Tukey, 1977). This literature includes multiple procedures and coefficients proposed to measure vertical collinearity (Douglass et al., 2003). More recently, vertical collinearity has been usually assessed through the calculation of a variance inflation factor (VIF) for each of the predictor latent variables, and the comparison of these VIFs with a threshold (Hair et al., 2009; Kline, 1998). The increasing use of the VIF as a measure of vertical collinearity has been enabled by the widespread use of powerful personal computers, as its calculation is fairly computing-intensive in models with multiple predictor variables.

Each VIF is calculated as indicated in Equation (1) where $i$ is an index that refers to each predictor variable in a regression equation containing only the predictors (i.e., excluding the criterion) in each block of variables in an SEM model. The term $R_i^2$ refers to the variance explained for each predictor (indexed by $i$) by all of the remaining predictors. As it can be seen, the VIFs are calculated independently of the criterion variable. That is, the VIFs take into consideration only the effects of the predictor variables on themselves.

$$(1)\quad VIF_i = \frac{1}{1 - R_i^2}$$

Situations in which variables are correlated yet not collinear are actually quite common in multivariate analyses (Echambadi & Hess, 2007; Hair et al., 2009). If correlation and collinearity always occurred together, no "real" causal effects would ever be supportable by multivariate analyses. In SEM, collinearity often stems from a mismatch between the research instrument designer's view of indicator-construct relationships and those of the respondents or data analysts. The latter may be researchers other than the instrument's designer.

For example, let us assume that a researcher designed a questionnaire assuming two constructs to be distinct, in an investigation on the success of product innovation teams. The two constructs are "team success in terms of sales" and "team success in terms of return on investment". The researcher developed question-statements associated with these two constructs, which were answered based on Likert-type scales. The answers led to two sets of indicators, which the researcher assumed to be associated with two distinct latent variables (i.e., "team success in terms of sales" and "team success in terms of return on investment").

A problem of collinearity would exist if the respondents perceived the two latent variables as measuring the "same thing". That is, if the respondents could not see the difference in the question-statements for the indicators used in each of the two latent variables in the same way that the researcher did. This "same thing" could be another construct such as "team success", which would have subsumed the two constructs in the eyes of the respondents.

## 5. Lateral Collinearity

Vertical collinearity is not the only type of collinearity that can distort the results of multivariate analyses, in general, and variance-based SEM analyses, in particular. In the same way that predictor variables may be collinear with each other, predictor variables may also be collinear with a criterion variable. That is, collinearity may occur in both the "vertical" and "lateral" directions in a block with multiple predictors pointing at one criterion variable.

Figure 2 illustrates the occurrence of lateral collinearity in the context of variance-based SEM. It shows a block with $n$ predictor latent variables $LVp_1$, $LVp_2$, $LVp_3 \dots LVp_n$ pointing at one criterion latent variable $LVc$. As mentioned before, any variance-based SEM model can be decomposed into multiple blocks like this. Here the collinearity is indicated as involving $LVp_3$ and $LVc$. (This is done for illustration purposes only; the collinearity could have involved more than one predictor.) That is, the collinearity occurs in a "lateral" way, which is why it is referred to here as "lateral collinearity".

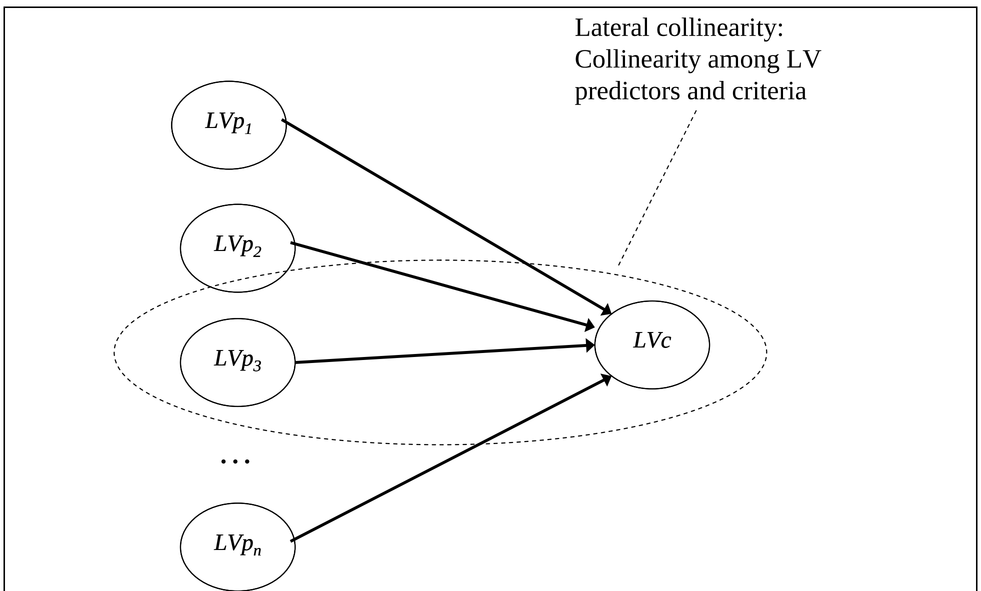



**Figure 2. Lateral Collinearity**

Lateral collinearity is almost never explicitly tested in multivariate analyses, nor is it explicitly addressed in widely used textbooks on multivariate analyses (Hair et al., 2009; Schumacker & Lomax, 2004), even though it can lead to very misleading conclusions. One of the reasons is that the variables in question do not point at any other variable, creating a problem for the calculation of VIFs (Hair et al., 2009; Kline, 1998).

Collinearity between $LVp_3$ and $LVc$ would have the effect of making the coefficient of association between these two latent variables appear to be very strong and statistically significant. This could lead to the misleading conclusion that $LVp_3$ is a strong predictor of $LVc$, when in reality, the strong association is due to both latent variables essentially measuring the same "thing" (i.e., the same construct). The conclusion that $LVp_3$ is a strong predictor of $LVc$ may, in turn, form the basis for misguided and possibly costly organizational decisions aimed at manipulating $LVp_3$ and $LVc$.

# 6. What VIF Threshold Should Be Used?

Much divergence exists in the literature regarding the VIF value to be used as the threshold for collinearity (Cenfetelli & Bassellier, 2009; Kline, 1998; Petter, Straub, & Rai, 2007). Commonly recommended values are 10, 5, and 3.3; meaning that a VIF equal to or greater than the threshold value would suggest the existence of collinearity among the variables (a.k.a. multicollinearity). Such divergence is problematic, because it makes it difficult to derive clear-cut methodological guidelines for researchers, and is in part due to the different contexts in which these values were proposed.

Hair et al. (2009, p.193) state that: "A common threshold is … a VIF value above 10". But, at the same time, they also state that: "Each researcher must determine the degree of collinearity that is acceptable, because most defaults or recommended thresholds still allow for substantial collinearity". The indirect message buried in such ambiguous advice is that a threshold of 10 should probably be considered a minimum threshold in multivariate models, in general, and that lower thresholds may be advisable under certain conditions.

Kline (1998) proposes a VIF threshold of 5 in the context of covariance-based SEM. It should be noted, however, that variance-based SEM employs PLS regression or variations of it for the calculation of the weights to be assigned to each indicator in a latent variable (Lohmöller, 1989; Wold et al., 2001). Even though PLS regression does not eliminate collinearity, it is particularly effective at minimizing it (Chin et al., 2003; Haenlein & Kaplan, 2004). Because of this, one could reasonably expect that a VIF threshold of 5 might be too high in variance-based SEM.

The VIF threshold of 3.3 has been recommended in the context of variance-based SEM, but in discussions of formative latent variable measurement (Cenfetelli & Bassellier, 2009; Petter et al., 2007). In these discussions, the threshold of 3.3 refers to the VIF values calculated for each of the indicators of a formative latent variable, where the indicators are seen as predictors of the latent variable score. This threshold does not refer to the VIF values for the scores of various latent variables that may be collinear, which is the main focus of this paper, and which would have been minimized via PLS regression. Therefore, even this threshold may well be too high for investigations aimed at uncovering lateral collinearity between latent variables in variance-based SEM.

The above point can be illustrated based on the minor effect that the introduction of moderating effects usually has in the VIF values calculated in the context of variance-based SEM. The addition of moderating effects tends to add collinearity to a SEM model, because the latent variables that represent the moderating effects are at least somewhat correlated with the pairs of variables that gave origin to them (Carte & Russel, 2003; Echambadi & Hess, 2007). Latent variables representing moderating effects are normally implemented as product-indicator interaction latent variables, based on the indicators of the moderating variable and the predictor variable of the predictor-criterion link that is being moderated (Chin et al., 2003).

However, the collinearity inflation caused by the introduction of moderating effects is countered by the collinearity minimization nature of the PLS regression algorithm, frequently leading to VIF values lower than 2 even with multiple moderating effects added (see Appendix G). This, of course, is based on the assumption that there would be no collinearity in the original model without the moderating effects; in such cases, the original VIF values would also typically be lower than 2.

Given the above discussion, we use the VIF value threshold of 3.3 in the remainder of this paper. That is, VIF values higher than 3.3 will be considered as indicative of collinearity, for the purposes of the arguments presented here, but with a caveat. This decision is accompanied by the caveat that more research is needed in the future to establish whether this threshold is truly adequate for collinearity tests involving multiple latent variables in the context of variance-based SEM. Such research is beyond the scope of this paper.

# 7. An Illustrative Example

The analysis used to illustrate the problem of lateral collinearity explored associations among several latent variables, which were conceptualized as attributes of teams engaged in product innovation efforts. The efforts led to the creation of new products or major redesign of existing products. The products comprised manufacturing goods, services, and information products. Teams had on average 24 individuals, were usually geographically dispersed, and used a variety of electronic communication media to support their work. We analyzed data from 290 innovation teams from organizations in the Northeastern USA.

Since the study is used for illustration purposes, it is not the goal here to provide a new empirical contribution through it. This should essentially be seen as a “toy” study, so to speak, even though it is based on reasonable assumptions so as to make it meaningful for information systems researchers. The main idea underlying the study was that a high degree of electronic communication media variety (i.e., use of a variety of technologies, each creating a communication medium with different characteristics) would be beneficial for the innovation teams; an idea that has been articulated by Watson-Manheim & Bélanger (2007).

According to this view, a high degree of electronic communication media variety would increase the teams’ ability to employ project management techniques and conduct their work efficiently, which would eventually lead to increased success in “bottom-line” aspects such as sales and return on investment (Bélanger & Watson-Manheim, 2006; Colazo & Fang, 2010; Kerzner, 2005; Watson-Manheim & Bélanger, 2002; Watson-Manheim & Bélanger, 2007).

Note that the focus of this particular investigation was on electronic communication media variety, not degree of overall electronic communication media use or its relationship with face-to-face communication. We expected the benefits to stem from a positive association between a team’s electronic communication media variety and the team’s ability to manage its work in a way that led to gains in efficiency. Those gains were expected to lead to downstream gains in team success, in terms of both sales and return on investment. These relationships are depicted in the model shown on Figure 3 (next page). Appendix C contains the measurement instrument used.

The latent variable electronic communication media variety (ECMV) refers to the number of tools reported as used “substantially” by each innovation team, where “substantially” means that the use of the tools was above the mid-point of their Likert-type use scales. Team project management (Prjmgt) refers to the extent to which an innovation team employed standard project management techniques to organize its work; for example, following a clear plan with milestones, and monitoring the team’s progress and associated costs. Team efficiency (Effic) refers to the extent to which a team met its original goals in terms of completion time and budget.

Team success in terms of sales (SSucce) refers to the extent to which a new product, developed by an innovation team, met or exceeded sales expectations. Team success in terms of return on investment (RSucce) refers to the extent to which a new product met or exceeded return on investment expectations. The hypothesized relationship between these two variables was based on the assumption that a product first has to sell well to generate a good return on investment; that is, without sales there can be no return on investment (Kerzner, 2005; Reich & Wee, 2006).

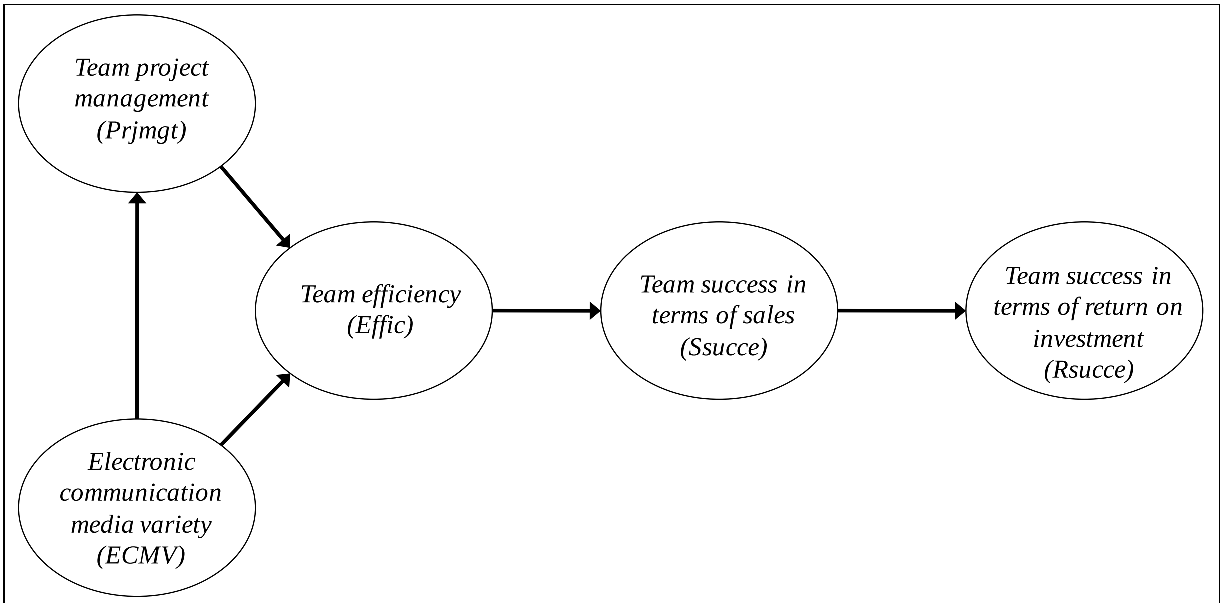



**Figure 3. Structural Model with Constructs**

We conducted the SEM analysis with the software WarpPLS 2.0 (Kock, 2011) and used PLS regression, which is one of the most effective multivariate algorithms used in variance-based SEM for minimization of collinearity (Haenlein & Kaplan, 2004; Hair et al., 2009; Jöreskog & Wold, 1982; Temme et al., 2006; Wold et al., 2001). The software conveniently calculates VIFs and several other parameters that can be used in a comprehensive and concurrent assessment of validity, reliability, and collinearity. As it will be shown, a model may contain "hidden" lateral collinearity and still pass standard tests of validity, reliability, and vertical collinearity.

Since WarpPLS is a relatively new software tool, we double-checked the results with three other statistical analysis software tools: MATLAB, SPSS, and PLS-Graph. (MATLAB is essentially a numeric computing tool with extensive support for statistical analyses.) These statistical software tools either generate partial results that must be combined to obtain the broader set of results discussed here (SPSS and PLS-Graph), or require extensive programming to be fully utilized in variance-based SEM (MATLAB). The results were essentially the same across different tools, suggesting consistency in the underlying algorithms employed.

## 8. The Distorting Effect Of Lateral Collinearity

The model with the main results is shown on Figure 4. The beta coefficients are standardized partial regression coefficients, and reflect the strength of the associations between pairs of linked latent variables. Beta coefficients noted with a "*" are significant at the P < .001 level; this includes all beta coefficients but one, the beta between ECMV and Effic, which was not statistically significant (P=.129). Nearly all beta coefficients are significant at the P < .001 level because of both the strength of the relationships and the relatively large sample size (N=290). R-squared coefficients are shown under criteria (a.k.a. endogenous) latent variables; they reflect the percentage of explained variance for those variables.

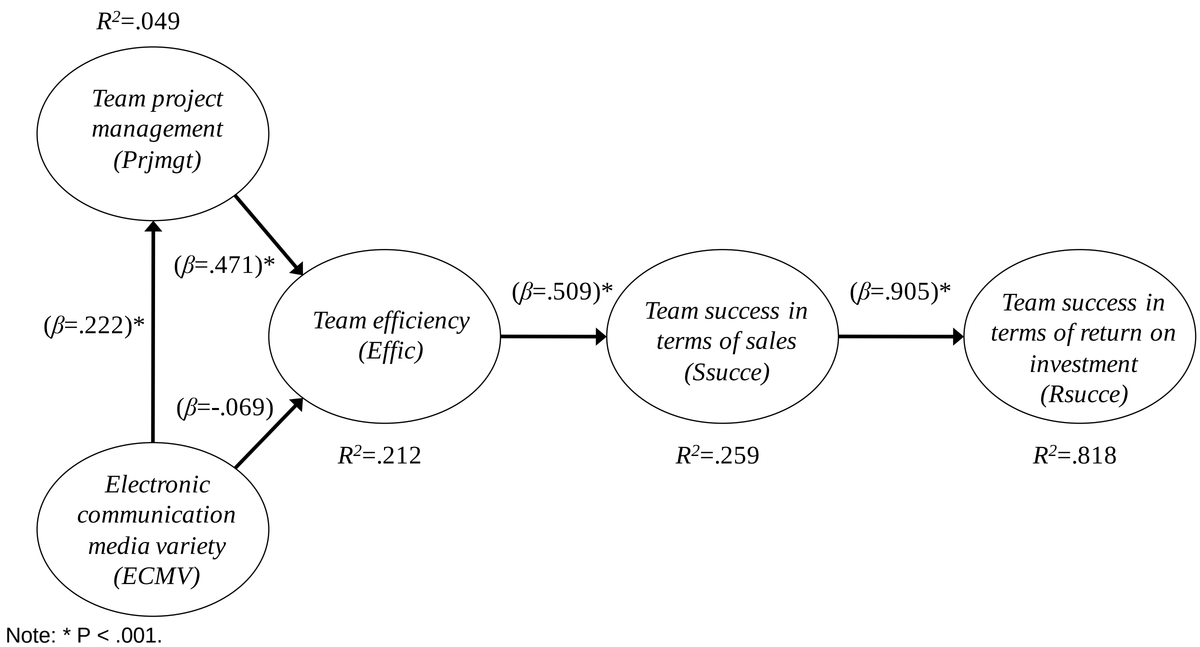



**Figure 4. Model with Main Results**

The results suggest that Prjmgt mediates the relationship between ECMV and Effic. The results also suggest that ECMV has a trivial effect on Effic, when the effect of Prjmgt is controlled for. Combined, these results are consistent with the general notion that electronic communication technologies often do not affect performance directly, but rather require some form of complex adaptive use to mediate their effect on performance (Briggs, De Vreede, & Nunamaker, 2003; Burke, Aytes, & Chidambaram, 2001; Dennis, Hayes, & Daniels, 1999; DeSanctis & Poole, 1994; Easley, Devaraj, & Crant, 2003; Fjermestad & Hiltz, 1998; Kahai & Cooper, 2003; Markus, 2005).

Note the particularly high beta coefficient between SSucce and RSucce (beta=.905), suggesting a strong and positive association. The resulting R-squared for RSucce is a high .818, suggesting that 81.8 percent of the variance in RSucce is explained by one single latent variable, namely SSucce. As it will be seen later, these high beta and R-squared coefficients are due to lateral collinearity, and the apparently strong causal association between SSucce and RSucce is a "mirage". Nevertheless, the measurement instrument and related dataset pass standard validity, reliability, and vertical collinearity tests. This is demonstrated in the next several paragraphs.

Table 1 (next page) shows indicator loadings, cross-loadings, and reliability measures. The loadings and cross-loadings are from a pattern matrix, obtained from a structure matrix by oblique rotation and without any normalization (Hair et al., 2009; Maruyama, 1998; Miller & Wichern, 1977). Loadings must be equal to or greater than .5 for convergent validity to be considered acceptable (Hair et al., 2009; Kline, 1998), which is the case here, meaning that there seems to be good agreement between the questionnaire designer and the respondents regarding the sets of indicators that "belong" to each latent variable.

For reliability to be considered acceptable, both the composite reliability (CR) and the Cronbach alpha (CA) coefficients should be equal to or greater than .7 (Fornell, & Larcker, 1981; Nunnaly, 1978), indicating good agreement among respondents regarding the meaning of each set of indicators belonging to a particular latent variable. This is also the case here, as the CRs and CAs are all above .805. In fact, the criterion that both CR and CA should be equal to or greater than .7 is a rather conservative criterion, not followed by all researchers. Many use only CR as a basis for this test, since CR is the only coefficient of reliability of the two that takes indicator loadings into consideration.

| Table 1. Indicator Loadings, Cross-Loadings and Reliability Measures | | | | | | | |
|---|---|---|---|---|---|---|---|
| | **ECMV** | **PMngt** | **Effic** | **SSucce** | **RSucce** | **CR** | **CA** |
| **ECMV** | (1.000) | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| **Prjmgt** | | | | | | 0.885 | 0.805 |
| **Prjmgt1** | -0.001 | (0.817) | 0.053 | 0.296 | -0.331 | | |
| **Prjmgt2** | -0.040 | (0.891) | -0.085 | -0.034 | 0.170 | | |
| **Prjmgt3** | 0.044 | (0.836) | 0.038 | -0.269 | 0.159 | | |
| **Effic** | | | | | | 0.925 | 0.897 |
| **Effic1** | -0.005 | -0.006 | (0.909) | -0.158 | 0.141 | | |
| **Effic2** | -0.064 | 0.053 | (0.928) | -0.372 | 0.247 | | |
| **Effic3** | 0.005 | 0.061 | (0.807) | -0.167 | 0.142 | | |
| **Effic4** | 0.079 | -0.146 | (0.888) | 0.483 | -0.502 | | |
| **Effic5** | -0.009 | 0.034 | (0.670) | 0.269 | -0.067 | | |
| **SSucce** | | | | | | 0.964 | 0.949 |
| **SSucce1** | -0.042 | 0.030 | -0.028 | (1.051) | -0.094 | | |
| **SSucce2** | 0.031 | -0.021 | -0.041 | (0.800) | 0.193 | | |
| **SSucce3** | 0.005 | -0.017 | 0.109 | (1.132) | -0.347 | | |
| **SSucce4** | 0.006 | 0.006 | -0.029 | (0.771) | 0.214 | | |
| **RSucce** | | | | | | 0.955 | 0.928 |
| **RSucce1** | 0.037 | -0.037 | -0.020 | -0.078 | (1.045) | | |
| **RSucce2** | 0.033 | 0.018 | -0.097 | -0.183 | (1.164) | | |
| **RSucce3** | -0.074 | 0.020 | 0.123 | 0.275 | (0.581) | | |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; SSucce: Team success in terms of sales; RSucce: Team success in terms of return on investment. Loadings shown within parentheses; CR: composite reliability coefficient; CA: Cronbach alpha coefficient. Loadings and cross-loadings are after an oblique rotation, and without normalization.

Even though we can conclude that the measurement instrument and related dataset present good convergent validity and reliability, note that some of the loadings for indicators belonging to the latent variables SSucce and RSucce are greater than 1. In pattern matrices that have not been normalized, this is not necessarily an indication of data abnormalities, even though it is sometimes associated with abnormalities (Hair et al., 2009). Examples of possible abnormalities that could cause this are linear dependence among variables, rank problems, outliers due to measurement error, highly nonlinear relationships being modeled as linear, and collinearity. Normalization would mask this, as it would ensure that all loadings are capped at 1 (Ehremberg & Goodhart, 1976; Miller & Wichern, 1977; Thompson, 2004). Still, one cannot say with certainty that there is a problem with the dataset, let alone that collinearity is the source of the possible problem. The “odd” loadings are nothing but a “red flag” at this point. Additional factor analysis results, illustrating other related red flags, are discussed in Appendix E.

Even if there were convergent validity and/or reliability problems, the question as to whether there were collinearity problems would remain open. Conceptually, collinearity is a different problem from those related to poor convergent validity or reliability (Hair et al., 2009; Kline, 1998). These problems are all somewhat related, but they are not the same. This caveat adds to the one, pointed out before, that collinearity is not the same as correlation (Echambadi & Hess, 2007; Hamilton, 1987). Two variables may be highly correlated but not collinear, even though two variables that are collinear will usually be highly correlated (see Appendix B for an extended discussion of correlation versus collinearity).

Table 2 shows correlations among latent variables and square-roots of the average variances extracted (AVEs) for each latent variable. The square-roots of the AVEs are shown on the diagonal and within parentheses. These coefficients are used to test the discriminant validity of the measurement instrument and related dataset, which is essentially the degree of agreement between questionnaire designer and respondents regarding the mismatch between sets of indicators "belonging" to certain latent variables and other, unrelated, latent variables. Or, in simpler terms, discriminant validity is the degree of agreement between questionnaire designer and respondents regarding indicators that do and do not "belong" to certain latent variables.

**Table 2. Latent Variable Correlations and Square-Roots of AVEs**

| | ECMV | Prjmgt | Effic | SSucce | RSucce |
|---|---|---|---|---|---|
| **ECMV** | (1.000) | 0.222 | 0.035 | 0.125 | 0.111 |
| **PMngt** | 0.222 | (0.848) | 0.456 | 0.353 | 0.313 |
| **Effic** | 0.035 | 0.456 | (0.843) | 0.509 | 0.516 |
| **SSucce** | 0.125 | 0.353 | 0.509 | (0.933) | 0.905 |
| **RSucce** | 0.111 | 0.313 | 0.516 | 0.905 | (0.936) |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; SSucce: Team success in terms of sales; RSucce: Team success in terms of return on investment. AVE: average variance extracted. Square-roots of AVEs shown on diagonal within parentheses.

A measurement instrument and related dataset are considered to have acceptable discriminant validity if the square-roots of the AVEs for each latent variable are higher than any of the correlations between that latent variable and other latent variables (Fornell & Larcker, 1981). This can be ascertained by comparing the numbers on the diagonal with the numbers above and below them, within each column. The numbers on the diagonal should always be higher, which is the case here, suggesting acceptable discriminant validity. Note that the square-root of the AVE for RSucce (.936) is not much higher than the high correlation between SSucce and RSucce (.905). Even though this is not enough for discriminant validity to be questioned, it is another red flag strongly indicative of collinearity because it refers to a very simple block with only one predictor pointing at the criterion latent variable (see Appendix B).

Table 3 shows the VIFs used in a vertical, or "classic", collinearity test. As noted before, vertical collinearity in SEM refers to collinearity among latent variable predictors in blocks where two or more predictors point at one criterion (or endogenous latent variable). In the model that served as the basis for this illustrative analysis, this happens only on the left part of the model, where both ECMV and Prjmgt point at Effic. VIFs lower than 3.3 suggest no vertical collinearity, which is the case here.

**Table 3. Vertical Collinearity Estimates**

| | ECMV | Prjmgt |
|---|---|---|
| **Effic** | 1.052 | 1.052 |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency. Since only vertical, or "classic", collinearity is assessed here, the VIFs shown are for the single block where two latent variable predictors point at a latent variable criterion in the model. VIFs lower than 3.3 suggest no collinearity.

The tests above are reasonably comprehensive in their scope. They check for validity, reliability, and vertical collinearity problems. They find no clear problems. A few red flags exist – e.g., high latent variable correlations (in comparison with AVEs), and pattern matrix loadings greater than 1. However, these red flags do not tell us with certainly that problems exist, according to widely used data validation tests, nor the types of problems that may exist. Moreover, lateral collinearity may exist even without these red flags, and lateral collinearity can lead to misleading conclusions by suggesting the existence of associations that do not actually exist in the real world.

# 9. Identifying Lateral Collinearity: A Full Collinearity Test

There are two main ways in which lateral collinearity can be identified. The first relies on the creation of multiple “dummy” blocks of latent variables, where predictor-criteria pairs point at dummy latent variables. The latter become the new criteria variables in the dummy blocks. As noted before, VIFs are not influenced in any way by the values of the criterion variable in a block. Therefore, the dummy variables can assume any values, including random values. That is, the VIFs for each predictor-criteria pair in a dummy block will be the same regardless of the values that the dummy variable stores.

The second main way in which lateral collinearity can be identified is to perform what is referred to here as a “full” collinearity test. This can be done by creating a block where all latent variables in the model are included as predictors pointing at one single criterion, a dummy variable. (See Appendix F for a discussion of how this can be implemented in practice.) This is a more comprehensive and conservative test of collinearity, since it allows for the identification of collinearity among all the variables in the model, regardless of where they are located in the model. Different latent variables refer to different constructs, whether they are in the same block on not in a SEM model. This renders this second approach particularly appealing, and, thus, it is the one we employ. Table 4 shows the results.

**Table 4. Full Collinearity Estimates**

| ECMV | Prjmgt | Effic | SSucce | RSucce |
|---|---|---|---|---|
| 1.067 | 1.366 | 1.593 | 5.700 | 5.668 |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; SSucce: Team success in terms of sales; RSucce: Team success in terms of return on investment. The VIFs shown are for all of the latent variables; a “dummy” latent variable criterion was used. VIFs equal to or greater than 3.3 suggest collinearity.

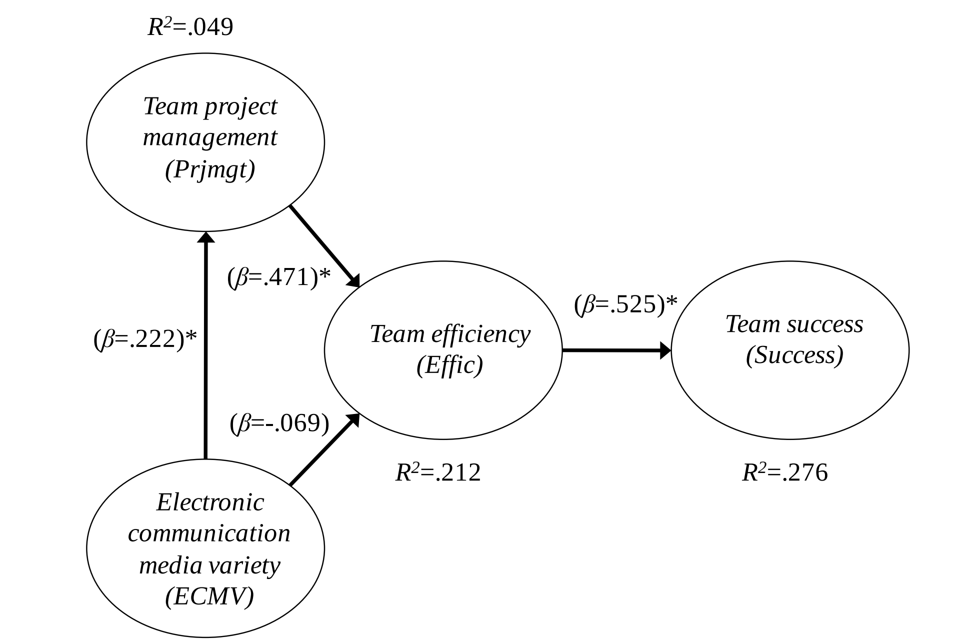
In a full collinearity test, VIFs equal to or greater than 3.3 suggest the existence of collinearity in the context of variance-based SEM. They frequently appear in pairs, as is the case here for SSucce and RSucce. Often collinearity in SEM is related to mistakes in questionnaire design or grouping of indicators that involve pairs of latent variables (Kline, 1998; Schumacker & Lomax, 2004). It is possible that mistakes in questionnaire design or grouping of indicators cause three or more latent variables to be collinear, although this may be less likely to occur in practice.

Investigations where indicators are grouped a posteriori based on the results of exploratory factor analyses may also be vulnerable in this respect (Ehremberg & Goodhart, 1976; Thompson, 2004). The reason is that exploratory factor analyses do not incorporate any semantic knowledge regarding indicators and their likely meaning, which is arguably important in their association with the “right” latent variables. This is illustrated in Appendix E, where indicators were incorrectly associated, or grouped, across two distinct factors (representing distinct candidate latent variables) as a result of an exploratory factor analysis where orthogonal rotation was employed.

# 10. Eliminating Lateral Collinearity: The New Results

Upon a careful review of the measurement instrument, it became apparent that the two latent variables SSucce and RSucce were included in the analysis by mistake, because the question statements associated with those two variables were originally designed to be associated with one single latent variable. That is, the designer of the questionnaire had only one construct in mind, but the researcher that conducted the data analysis (a different person) saw two possible constructs upon review of the questionnaire. The analyst's view was supported by reliability, validity, and vertical collinearity tests. However, it was not supported by a full collinearity test, which identified lateral collinearity, eventually supporting the questionnaire designer's view.

Given the above, one solution to the collinearity problem would be to combine the two offending latent variables, SSucce and RSucce, into one. This new latent variable would be Success, and would refer to team success, in general, not success only in terms of sales or return on investment (see Appendix D). Figure 5 displays the new model where this solution is implemented; with recalculated beta coefficients, respective P values, and R-squared values.




Note: * P < .001.

**Figure 5. New Model with Main Results**

Instead of combining the two offending latent variables into one, an alternative solution would be to remove one of the redundant latent variables from the model. However, even if this latent variable removal solution were suggested as appropriate after a careful review of the questionnaire and the process that led to its design, it could possibly be a less advisable solution, as it would lead to fewer indicators being used in the analysis. Generally speaking, the more indicators are used per latent variable in a SEM analysis, the greater is the opportunity for minimization of measurement error (Fornell & Bookstein, 1982; Kline, 1998; Schumacker & Lomax, 2004). Other solutions exist, such as conducting a hierarchical analysis; we discuss this and other solutions later.

The new configuration of latent variables and related indicators leads to new loadings, cross-loadings, and reliability coefficients (see Table 5). As in the previous model, the one with lateral collinearity problems, these suggest acceptable convergent validity (loadings equal to or greater than .5; Hair et al., 2009; Kline, 1998) and reliability (CRs and CAs equal to or greater than .7; Fornell, & Larcker, 1981; Nunnaly, 1978). It is worth noting that, in contrast to the previous model, no loadings greater than 1 are present in the pattern matrix, even though loadings are not normalized.

| Table 5. Indicator Loadings, Cross-Loadings and Reliability Measures | | | | | | |
|---|---|---|---|---|---|---|
| | **ECUVar** | **Prjmgt** | **Effic** | **Success** | **CR** | **CA** |
| **ECUVari** | 1.000 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| **Prjmgt** | | | | | 0.885 | 0.805 |
| **Prjmgt1** | -0.001 | (0.836) | 0.039 | -0.030 | | |
| **Prjmgt2** | -0.040 | (0.884) | -0.081 | 0.130 | | |
| **Prjmgt3** | 0.044 | (0.824) | 0.047 | -0.111 | | |
| **Effic** | | | | | 0.925 | 0.897 |
| **Effic1** | -0.006 | -0.014 | (0.915) | -0.019 | | |
| **Effic2** | -0.065 | 0.035 | (0.941) | -0.126 | | |
| **Effic3** | 0.005 | 0.052 | (0.814) | -0.026 | | |
| **Effic4** | 0.079 | -0.117 | (0.867) | -0.011 | | |
| **Effic5** | -0.008 | 0.043 | (0.663) | 0.200 | | |
| **Success** | | | | | 0.972 | 0.966 |
| **Success1** | -0.041 | 0.060 | -0.050 | (0.942) | | |
| **Success2** | 0.032 | -0.007 | -0.051 | (0.973) | | |
| **Success3** | 0.006 | 0.024 | 0.080 | (0.777) | | |
| **Success4** | 0.007 | 0.018 | -0.038 | (0.965) | | |
| **Success5** | 0.036 | -0.075 | 0.006 | (0.935) | | |
| **Success6** | 0.032 | -0.026 | -0.066 | (0.947) | | |
| **Success7** | -0.074 | 0.007 | 0.132 | (0.832) | | |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; Success: Team success. Loadings shown within parentheses; CR: composite reliability coefficient; CA: Cronbach alpha coefficient. Loadings and cross-loadings are after an oblique rotation, and without normalization.

Table 6 shows the new latent variable correlations and square-roots of AVEs. Like in the previous model with lateral collinearity problems, the figures on the table suggest acceptable discriminant validity (the square-roots of the AVEs for each latent variable are higher than any of the correlations between that latent variable and other latent variables; Fornell & Larcker, 1981). In contrast to the previous model, there is no instance in which a square-root of AVE for a latent variable is almost the same as a correlation between that latent variable and another latent variable.

| Table 6. Latent Variable Correlations and Square-Roots of AVEs | | | | |
|---|---|---|---|---|
| | **ECMV** | **Prjmgt** | **Effic** | **Success** |
| **ECMV** | (1.000) | 0.222 | 0.035 | 0.122 |
| **PMngt** | 0.222 | (0.848) | 0.456 | 0.344 |
| **Effic** | 0.035 | 0.456 | (0.843) | 0.525 |
| **Success** | 0.122 | 0.344 | 0.525 | (0.912) |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; Success: Team success. Square-roots of AVEs shown on diagonal within parentheses.

If we were to use the same vertical collinearity test employed in the previous model, the results would be the same. This is because the only block where two or more predictors point at a criterion is the same. Instead, Table 7 shows the VIFs generated from a full collinearity test, which captures any possible vertical or lateral collinearity problems. No collinearity exists in the new model (VIFs are lower than 3.3).

**Table 7. Full Collinearity Estimates**

| ECMV | Prjmgt | Effic | Success |
|---|---|---|---|
| 1.067 | 1.351 | 1.585 | 1.420 |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; Success: Team success. The VIFs shown are for all of the latent variables; a "dummy" latent variable criterion was used. VIFs lower than 3.3 suggest no collinearity.

In summary, lateral collinearity problems cannot normally be identified based on standard validity, reliability, or vertical collinearity tests. Still, lateral collinearity can lead to misleading conclusions. Strong predictor-criterion effects in SEM and other statistical analysis tests may appear to exist, being essentially a mirage caused by lateral collinearity. These can be particularly problematic in multivariate analyses, even though they may also occur in bivariate (a.k.a. univariate) analyses.

Based on this, it is strongly recommended that full collinearity tests be conducted in future empirical research, together with validity and reliability tests. Full collinearity tests capture both vertical and lateral collinearity problems. This recommendation applies not only to the field of information systems, but to all fields that employ multivariate data analysis methods. Moreover, a full collinearity test may be seen as a variance-based SEM equivalent to a test frequently used in covariance-based SEM known as common method bias test (Lindell & Whitney, 2001), and be used also to rule out that type of bias based on the same criterion for absence of collinearity.

# 11. Discussion and Recommendations

This section provides a broad discussion of possible causes and signs of collinearity, as well as recommendations on ways to deal with collinearity. For completeness, it addresses collinearity, in general; lateral as well as vertical collinearity. Emphasis is placed on variance-based SEM, even though at least part of the discussion applies to other multivariate analysis methods.

## 11.1. Causes of Collinearity

One of the most extensive discussions of general causes of collinearity is the one laid out by Mosteller & Tukey (1977) in their seminal book on data analysis and regression. However, it refers only to vertical collinearity and mostly in the context of manifest variables, as opposed to latent variables. Hair at al. (2009) provide a more succinct list of possible causes of vertical collinearity based on an extensive survey of the literature, again with an emphasis on manifest variables.

The focus of this paper is on latent variables in variance-based SEM analyses. Within this sphere of application, and taking various related developments in the literature on collinearity into consideration (Echambadi & Hess, 2007; Graham, 2003; Hair at al., 2009; Mosteller & Tukey, 1977; Sengupta & Bhimasankaram, 1997), it seems that two fundamental and generic reasons for collinearity are construct mismatch and redundant latent variables.

### *11.1.1. Construct Mismatch*

The definition of construct used here is that of a mental representation of an attribute of an object (Audi, 2003; Popper, 1992). A researcher designing a questionnaire may have certain mental representations of object attributes, such as satisfaction with and intention to use a particular technology, while the respondents of the questionnaire may have different mental representations of those object attributes. For example, a researcher may view two constructs as separate, whereas the respondents may provide answers to a questionnaire suggesting that they view those two constructs as being part of the same broader construct. Construct mismatch may also occur among different members of a research team, such as a questionnaire designer and a data analyst. A different but related construct mismatch situation would be one in which the researcher sees two or more constructs as separate, whereas the respondents see the constructs as instances of a higher order construct (Wetzels, Odekerken-Schroder, & van Oppen, 2009).

#### *11.1.2. Redundant Latent Variables*

Two variables are said to be redundant if they measure the same construct in situations where there is no construct mismatch – for example, the researcher and the respondents are in agreement, even if unknowingly, regarding their mental representations of the object attributes addressed through the research. In variance-based SEM, redundancy is often desirable only among indicators of the same latent variable, if the variable is measured reflectively as opposed to formatively (Gefen et al., 2000; Petter et al., 2007). Redundancy among latent variables is a possible cause of collinearity in variance-based SEM, and may result from treating multiple measures of the same construct as if they were measures of different constructs. Let us assume that a researcher decided to study the effect that perceived and actual wealth had on the choice of personal mobile technology used. The researcher included two latent variables in an SEM model, treating them as distinct variables: perceived wealth, measured through 5 indicators; and actual wealth, measured as a composite of 3 objective measures of wealth (e.g., net worth). If perceived wealth were a very good proxy for actual wealth, then the two latent variables would be redundant and, thus, add collinearity to the model. If the two variables were included in a predictor-criterion block, actual wealth as predictor and perceived wealth as criterion, this would lead to lateral collinearity.

## 11.2. Signs of Collinearity

The main signs of collinearity in variance-based SEM are the following: high R-squared coefficients, high correlations among latent variables, loadings greater than 1 after a non-normalized oblique rotation in a confirmatory factor analysis, unrotated cross-loadings greater than .5 in a confirmatory factor analysis, unexpected groupings of indicators after an orthogonal rotation in an exploratory factor analysis, and path coefficients greater than 1 or lower than -1.

#### *11.2.1. High R-Squared Coefficients*

As discussed earlier, the VIF for a criterion latent variable in a latent variable block (a.k.a. an endogenous latent variable) is a function of the variance explained by the predictor latent variables. The VIF threshold of 3.3 is reached for an R-squared of .697, or .835 to the power of 2 (see Appendix B). Therefore, an R-squared of .697 or greater is a sign of lateral collinearity in the context of variance-based SEM. It is not a guarantee of lateral collinearity though, because path coefficients (i.e., betas) for links between predictors and criteria may be inflated due to vertical collinearity (Mueller, 1996), leading to inflated R-squared values. In the illustrative example, the R-squared for the criterion among the two collinear latent variables was .818 (greater than .697) and, thus, suggestive of lateral collinearity.

#### *11.2.2. High Correlations Among Latent Variables*

Correlation is a necessary but insufficient condition for collinearity to exist. Moreover, the relationship between correlation and collinearity is nonlinear. Nevertheless, in very simple variance-based SEM model blocks, with only two laterally connected latent variables, a correlation of .835 will most likely be associated with collinearity (see Appendix B). This was exemplified in the illustrative example, where the correlation between two latent variables in one such simple model was found to be .905. For more complex models, however, much lower correlation values may be associated with collinearity.

#### *11.2.3. Loadings Greater Than 1 (oblique-rotated CFA)*

Confirmatory factor analysis is usually an integral part of variance-based SEM, whereby loadings and cross-loadings are generated and subsequently used in data validation tests. After a non-normalized oblique rotation of loadings and cross-loadings, the existence of loadings greater than 1 is an indication of possible collinearity (Hair et al., 2009). The illustrative analysis exemplified this; in it, loadings greater than 1 were associated with some of the indicators of the two collinear latent variables.

### 11.2.4. Cross-Loadings Greater Than .5 (Unrotated CFA)

Usually one of the outputs of a confirmatory factor analysis is an unrotated table of loadings and cross-loadings, often referred to as a “structure matrix”. In the context of variance-based SEM, the loadings and cross-loadings in this table are bivariate correlations among indicators and latent variable scores. The threshold for an indicator to be considered as “belonging” to a latent variable is .5, and is applied to loadings in convergent validity assessment (Hair et al., 2009; Kline, 1998). Cross-loadings greater than .5 are signs of possible collinearity, as they reflect high correlations among a latent variable score and indicators that are not supposed to “belong” with that latent variable. This was shown in the illustrative example (more specifically, in Appendix E), where cross-loadings greater than .7 were associated with the two collinear latent variables.

### 11.2.5. Unexpected Groupings Of Indicators (Orthogonally Rotated EFA)

Orthogonal rotation of loadings and cross-loadings in confirmatory factor analysis is less frequently recommended than oblique rotation when latent variables are expected to be correlated (Ferguson, 1981; Thompson, 2004), which is the default expectation in variance-based SEM. Thus, tables with orthogonally rotated loadings and cross-loadings are not normally available as outputs in variance-based SEM software. However, an exploratory factor analysis may be conducted with generic statistical analysis software (e.g., SPSS). In an exploratory factor analysis employing an orthogonal rotation algorithm, unexpected groupings of indicators are indicative of possible collinearity. This occurred in the illustrative analysis (see Appendix E).

### 11.2.6. Path Coefficients Greater Than 1 or Lower Than -1

Path coefficients in variance-based SEM are standardized partial regression coefficients, of the same type as the standardized coefficients of association calculated though multiple regression analyses. They may become greater than 1 or lower than minus 1, typically due to vertical collinearity (Miller & Wichern, 1977). Given that PLS regression minimizes collinearity among latent variables, path coefficients greater than 1 or lower than minus 1 should not be common in variance-based SEM models. When they occur, one should expect to uncover the existence of vertical collinearity.

## 11.3. Dealing with Collinearity

It is recommended that full collinearity tests, as demonstrated in the illustrative example, be included as part of routine data validation tests in future information systems research employing variance-based SEM. Not only would this reduce the likelihood of collinearity-related problems, but also add rigor to variance-based SEM research by including the equivalent to a data validation test commonly employed in covariance-based SEM known as a common method bias test (Lindell & Whitney, 2001), which is not normally employed in variance-based SEM. This recommendation regarding full collinearity tests applies to disciplines other than information systems as well.

Moreover, it is recommended that datasets used in past variance-based SEM research where the above signs of collinearity are present be formally tested for collinearity, employing a full collinearity test as demonstrated in the illustrative example (see also Appendix F). If the existence of collinearity is confirmed, models should be revised, additional analyses conducted on the same dataset, and conclusions revisited. Four main approaches may be employed in this respect: indicator removal, indicator re-assignment, latent variable removal, latent variable aggregation, and hierarchical analysis. These are discussed below, in terms of collinearity between pairs of latent variables, but the discussion also applies to collinearity among three or more latent variables.

### 11.3.1. Indicator Removal

Collinearity between a pair of latent variables may be associated with a few offending indicators that are highly correlated with both latent variable scores. This would typically be seen in reflective latent variables, and would be indicated by high unrotated loadings and cross-loadings for those indicators from a confirmation factor analysis. In this case, a possible solution would simply be the removal of the offending indicators from the model.

### *11.3.2. Indicator Re-assignment*

Collinearity between a pair of latent variables may also be associated with a few offending indicators that are poorly correlated with the latent variable they were assigned to and highly correlated with the other latent variable. This may happen with reflective and formative latent variables. The offending indicators would be reflected through low loadings and high cross-loadings in both oblique-rotated and unrotated tables. In this case, a possible solution would be to re-assign the offending indicators.

### *11.3.3. Latent Variable Removal*

It is possible that collinearity between a pair of latent variables is due to all of the indicators of one or the other, or of both variables, being highly correlated with both latent variable scores. This would typically happen with reflective latent variable measurement. Situations in which latent variables are measured through a small number of indicators, including one single indicator, are the most likely to characterize this scenario. A possible solution is to remove one of the latent variables from the model.

### *11.3.4. Latent Variable Aggregation*

There is another possible solution to the above situation, where collinearity between a pair of reflective latent variables is due to all of the indicators of one or the other, or of both variables, being highly correlated with both latent variable scores. The solution is to aggregate all of the indicators of the collinear latent variables into one latent variable. The end result would be a model with fewer latent variables, as with the latent variable removal solution, but with more indicators being used in its measurement.

### *11.3.5. Hierarchical Analysis*

When formative latent variables are used, in some cases collinearity between a pair of latent variables may be associated with indicators that are poorly correlated with the latent variable they were assigned to and highly correlated with the other latent variable. In this case, a possible solution is to conduct a hierarchical analysis in two steps. The first would entail exploratory and confirmatory factor analyses involving only the formative latent variable, where the latent variable would be decomposed into two or more latent variables. In the second step, the latent variable scores obtained in the first step would be used as indicators of another latent variable, called a second-order latent variable, in the original model. This would likely reduce the collinearity in the original model. For very complex formative latent variables, this process could be extrapolated to multiple levels, leading to third-order, fourth-order, and so on latent variables being generated.

Model revision and additional analyses can lead to radically different conclusions, with important implications for research and practice. In some cases they may lead to significant revisions in theoretical models. It would take courage for researchers to engage in this process and admit to prior mistakes, such as having argued that strong causal relationships existed when those relationships were, in fact, artificial products of lateral collinearity. Still, that seems to be a better alternative than having those mistakes convincingly pointed out by others.

## 11.4. Additional Considerations

One might argue that the example with lateral collinearity in this paper was not properly supported by theory. While this may be true, the fragmentation of empirical research and theoretical models in the field of information systems (as well as in other fields where multivariate analyses are employed) makes it relatively easy to support the development of almost any set of hypotheses. Novel but wrong hypotheses may survive the review process due to being perceived as “fresh” and/or “interesting” by open-minded reviewers. Lateral collinearity, if not identified, may elevate those wrong hypotheses to the status of a “counterintuitive” and “groundbreaking” new theory, leading to even more fragmentation.

It could also be argued that lateral collinearity should be avoided by attacking the problem at its source: namely, the design of measurement instruments. Indeed, if a questionnaire is poorly designed, the techniques discussed here may not be enough to salvage the resulting dataset; they will only uncover problems. However, even a properly designed measurement instrument may lead to collinearity. This can happen if the respondents have an understanding of the meaning of certain question-statements that is different from that intended by the designer of the measurement instrument. In fact, collinearity may be caused by subtle differences in understanding, whose distorting effects could be greatly amplified through multivariate analyses. For example, the designer may have a slightly more sophisticated view of the difference between two or more constructs than the respondents, which may, in turn, give rise to severe collinearity.

Finally, one could argue that validity and reliability tests are enough to identify collinearity, as suggested by the red flags that emerged in the illustrative analysis. It is possible that red flags, such as oblique-rotated loadings higher than 1, will emerge through standard validity and reliability tests. But there are many problems associated with using them to identify collinearity. As demonstrated in the illustrative analysis, those red flags may not point clearly at collinearity as the underlying problem. Also, they may be masked by other commonly used statistical techniques, such as normalization (combined with rotation) of loadings and cross-loadings, and not even show up in tests. Finally, those red flags, while visible to researchers experienced in multivariate data analyses, do not violate criteria widely used in validity and reliability tests.

# 12. Conclusion

Vertical collinearity is a classic type of collinearity in that it is traditionally assessed in multiple regression analyses (Echambadi & Hess, 2007; Hair et al., 2009). We argue that there is another type of collinearity that is almost never assessed: namely, lateral collinearity. An example analysis is used to illustrate lateral collinearity, the problems that it creates, and related methodological solutions.

One key implication that stems from the discussion presented here is that information systems researchers, as well as researchers in several other fields, should conduct full collinearity tests in addition to validity and reliability tests in variance-based SEM analyses. Full collinearity tests are also indicated in multivariate analyses that do not employ latent variables, such as path and multiple regression analyses. It is clear that collinearity may severely distort results, while not being easy to identify through validity and reliability tests.

Given that, researchers may have to revisit previous analyses, and revise their findings if hidden collinearity existed but was not explicitly recognized. It is strongly recommended that analyses suggesting strong predictor-criterion associations be considered for full collinearity tests, as these are the types of associations that can normally be distorted by lateral collinearity.

The identification of strong predictor-criterion associations that do not exist is particularly problematic for practitioners. Those associations are often reported as supporting strong causation, which may lead practitioners to prioritize their business decisions in a misguided way. For example, let us assume that a predictor variable P is found to strongly influence a criterion C, where C refers to return on investment. But this is due to collinearity between P and C; something that is unknown to a researcher, who infers strong causation from this result. Based on the reported finding that P strongly influences C, a manager may feel compelled to maximize P in order to maximize C, at the expense of other possible predictors. This may lead to costly and mistaken organizational decisions, even as P and C grow together. The reason why P and C grow together is that they are essentially the same thing.

In the detailed illustrative analysis discussed earlier, one initial conclusion (due to collinearity) was that team success in terms of sales seemed to strongly influence team success in terms of return on investment. The underlying hypothesized relationship was based on the reasonable assumption that a product first has to sell well to generate a good return on investment (Kerzner, 2005; Reich & Wee, 2006). This highlights the possibility that good theory may lead to distorted results in the absence of appropriate lateral collinearity assessment.

Misleading findings due to lateral collinearity can be either difficult to implement by business practitioners, or lead to misguided business implementation decisions. Revised findings after removal of lateral collinearity may in the least provide a more focused basis on which practitioners can make decisions. In the illustrative analysis, after lateral collinearity was revealed, it appears that the foci of practitioners using the analysis to guide them should be on increasing the electronic communication media variety available to teams, while at the same time encouraging the use of project management techniques, which should, in turn, increase team efficiency and eventually team success.

Even though information systems is a relatively new field, it appears to have become a reference field for a variety of other fields (Baskerville & Myers, 2002; Grover et al., 2006), within and outside business. There are two main reasons for that. Not only is the field of information systems multidisciplinary, but information systems researchers are themselves multidisciplinary. In order to effectively do research, information systems researchers often have to combine knowledge from various fields. Examples of such fields are statistics, organizational behavior, computer science, and psychology. This places information systems researchers in a position where they can contribute to those fields as well; e.g., by developing both new statistical analysis techniques and the software tools that automate them, which may be used by organizational behavior and psychology researchers.

The stage is then set for information systems researchers to make methodological contributions that are relevant for the field of information systems and many other fields. A good example is the leadership role played by information systems researchers in the development of ideas, techniques, and software tools for variance-based SEM (Chin, 1998; Chin et al., 2003). Those are now increasingly used within and outside the field of information systems. The discussion presented here aims at making an interdisciplinary contribution that is very relevant for the field of information systems, and that is also arguably very relevant to many other fields. As such, the discussion present here is likely to contribute to strengthening information systems' position as a reference field.

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# Appendices

## Appendix A: Glossary

### *Correlation*

Correlation is fundamentally defined as a bivariate (a.k.a. univariate) phenomenon. Two variables are said to be correlated if they vary in concert. Correlation values may vary from -1 to 1. The presence of correlation is a necessary but insufficient condition to characterize collinearity.

### *Collinearity*

Collinearity is fundamentally a multivariate phenomenon, unlike correlation, which is fundamentally a bivariate phenomenon. Two or more variables are said to be collinear if they measure the same attribute of a tangible or intangible object. The term "multicollinearity" is often used as synonymous with collinearity.

### *Construct*

A construct is defined as a mental representation of an attribute of an object. For example, the object may be a technology, and the attribute may be ease of use. As such, there can be no construct without a mind, and the nature of a construct may vary across different individuals (and, thus, different minds). For example, a researcher designing a questionnaire may have one mental representation of an object's attribute, such as ease of use of a particular information technology, but the respondents of the questionnaire may have a different mental representation of that object's attribute.

### *Covariance-Based SEM*

Covariance-based SEM is the classic form of SEM, with many years of development and maturation. It relies on parametric assumptions about the data for the estimation of chance probabilities (typically in the form of P values), including the assumption of multivariate normality.

### *Factor*

A factor is an aggregation of manifest variables; the term "latent variable" is often used as synonymous with factor. Through factors, a dataset with multiple variables can be reduced to a more manageable set, and measurement error can be minimized.

### *Factor Analysis*

Factor analysis is a procedure through which variables in a dataset are reduced to factors, which are essentially aggregations of sets of original variables; the latter are often called indicators. Factor analysis can be exploratory, whereby factors are extracted from the dataset, or confirmatory, whereby factor-indicator relationships are specified beforehand and tested based on coefficients of association (e.g., loadings).

### *Formative Latent Variable*

In a formative latent variable the indicators refer to different facets of the same attribute of a tangible or intangible object, as opposed to being reflections of the same attribute. Generally speaking, indicators of a formative latent variable are expected to be significantly associated with the latent variable score, but are not expected to be redundant.

### *Indicator*

Indicators are manifest variables that are aggregated to form latent variables. In variance-based SEM, latent variable scores are calculated by aggregating indicators based on their weights. A weight is the standardized partial regression coefficient between the indicator and the latent variable score, and the latent variable score is calculated as the exact linear combination of its indicators based on their respective weights.

### *Latent Variable*

A latent variable is a variable that is not measured directly. A latent variable is measured indirectly through the aggregation of directly measured variables, often referred to as manifest variables or indicators.

### Lateral Collinearity

Lateral collinearity is predictor-criterion collinearity. That is, in graphical depictions of blocks involving multiple predictors and one criterion variable, it occurs in a “lateral” way, and is, thus, distinguished from vertical collinearity. Lateral collinearity is almost never explicitly tested in multivariate analyses. It is not explicitly addressed in widely used textbooks on multivariate analyses either, even though it can lead to very misleading conclusions.

### Manifest Variable

Manifest variables are measured directly, which differentiates them from latent variables. In survey research, manifest variables are often measured based on answers to questions on Likert-type scales. The questions are meant to refer to similar mental representations held by the researcher (usually the designer of the questionnaire) and the respondents and to cluster around latent variables.

### Redundancy

Redundancy is a property of different variables that measure the same attribute of a tangible or intangible object. Typically, variables that are redundant are also collinear; a measure of collinearity can be seen as a measure of the degree of redundancy of two or more variables.

### Reflective Latent Variable

In a reflective latent variable the indicators are reflections of the same attribute of a tangible or intangible object, as opposed to being different facets of the same object. Generally speaking, indicators of reflective latent variables are expected to be redundant.

### Structural Equation Modeling (SEM)

SEM can be defined as path analysis with latent variables, whereas each variable in a path model is measured through multiple “indicators” (e.g., multiple questions referring to the same construct in a questionnaire).

### Variance-Based SEM

Variance-based SEM is a more recent, sometimes referred to as “soft”, form of SEM. It relies on nonparametric, and thus, more flexible, assumptions about the data for the estimation of chance probabilities (typically in the form of P values). For example, that estimation does not build on the assumption of multivariate normality.

### Variance Inflation Factor (VIF)

The VIF is a multivariate measure that is a function of the variance explained on a variable by a set of variables, usually in the same model. Typically, a VIF is calculated for each of the predictors of a block of variables involving multiple predictors and one criterion.

### Vertical Collinearity

Vertical collinearity is a “classic” type of collinearity in that it is traditionally assessed in multiple regression analyses. Multiple regression analyses estimate coefficients of association between multiple predictor variables (a.k.a. independent variables) and one criterion variable (a.k.a. dependent variable). In this context, vertical collinearity refers to predictor-predictor collinearity.

## Appendix B: Correlation Versus Collinearity

As discussed earlier, the degree of collinearity of a latent variable $LV_1$ among a set of variables $LV_1$, $LV_2$, $\cdots LV_n$ is usually measured through the VIF for that latent variable. The VIF is itself is a function of the R coefficient for the latent variable, which is the square root of the variance explained in $LV_1$ by the variables $LV_2$, $LV_3 \cdots LV_n$.

This applies to any number of variables, and also to latent variables measured through only one indicator; the latter would not, technically speaking, be "true" latent variables. If only two variables are present, one predictor and one criterion, R would essentially be the correlation between the two variables.

Figure B-1 shows the relationship between VIF and R when only two variables are present. As it can be seen, the relationship is nonlinear. The curve is based on the equation relating VIF and R presented earlier – Equation (1). The values for VIF remain somewhat low and stable for values of R between 0 and .8, going up steeply afterwards. (Negative values of R would lead to the same curve, as VIF is a function of R squared.)

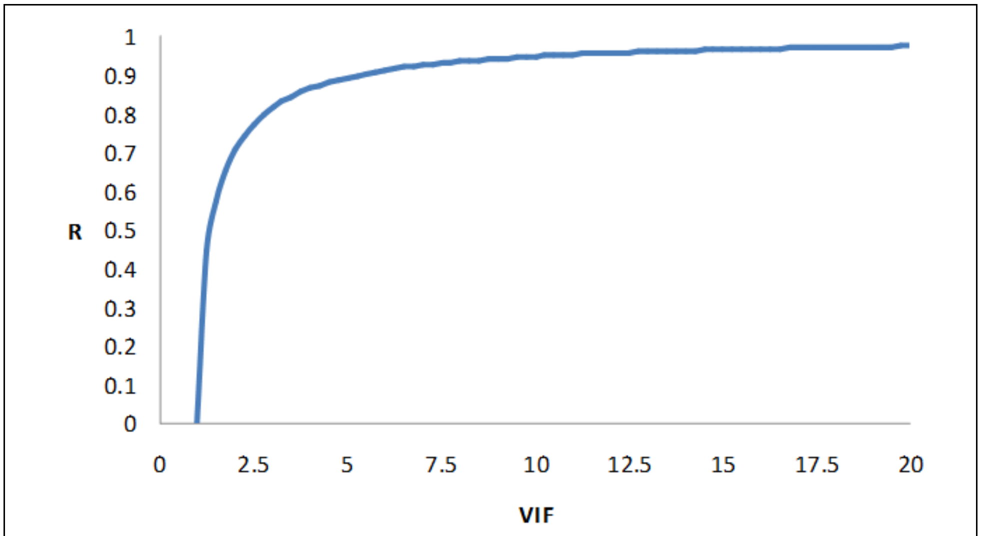



**Figure B-1. The Relationship Between VIF and R for Two Variables**

Table B-1 shows the values of VIF and R when only two variables are present. The lowest possible value for the VIF is 1, which occurs when R is 0. Let us assume that we were to set the threshold of VIF for collinearity at 3.3. In this case, a correlation of .835 or higher would suggest collinearity in a situation involving only two variables. Any block in an SEM model with only two variables, one predictor and one criterion, would characterize this correlation-collinearity coexistence situation.

**Table B-1. The Values of VIF and R for Two Variables**

| **VIF** | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.50 | 3.30 | 5.00 | 10.00 |
|---|---|---|---|---|---|---|---|---|---|
| **R** | 0.000 | 0.447 | 0.577 | 0.655 | 0.707 | 0.775 | 0.835 | 0.894 | 0.949 |

When more than two variables are involved, the analysis becomes much more complex, because now the R is a function of multiple variables, and essentially of multiple correlation values (Hair et al., 2009).

Let us consider a theoretical case in which two predictor variables point at a criterion variable, and the predictor variables are uncorrelated. In this case, the value of R for the criterion variable will be a function of two other correlation values, $R_1$ and $R_2$, which are the correlations between each of the predictor variables and the criterion. The value of VIF, which is itself a function of R, will consequently be a function of $R_1$ and $R_2$.

The values of VIF for the scenario above are plotted on Figure B-2, generated based on a simulation with MATLAB. Three dimensions are needed because three variables are involved. As it can be seen, the variable VIF can reach unacceptably high values, clearly suggestive of collinearity, for much lower values of $R_1$ and $R_2$ than in the case when only two variables are present.

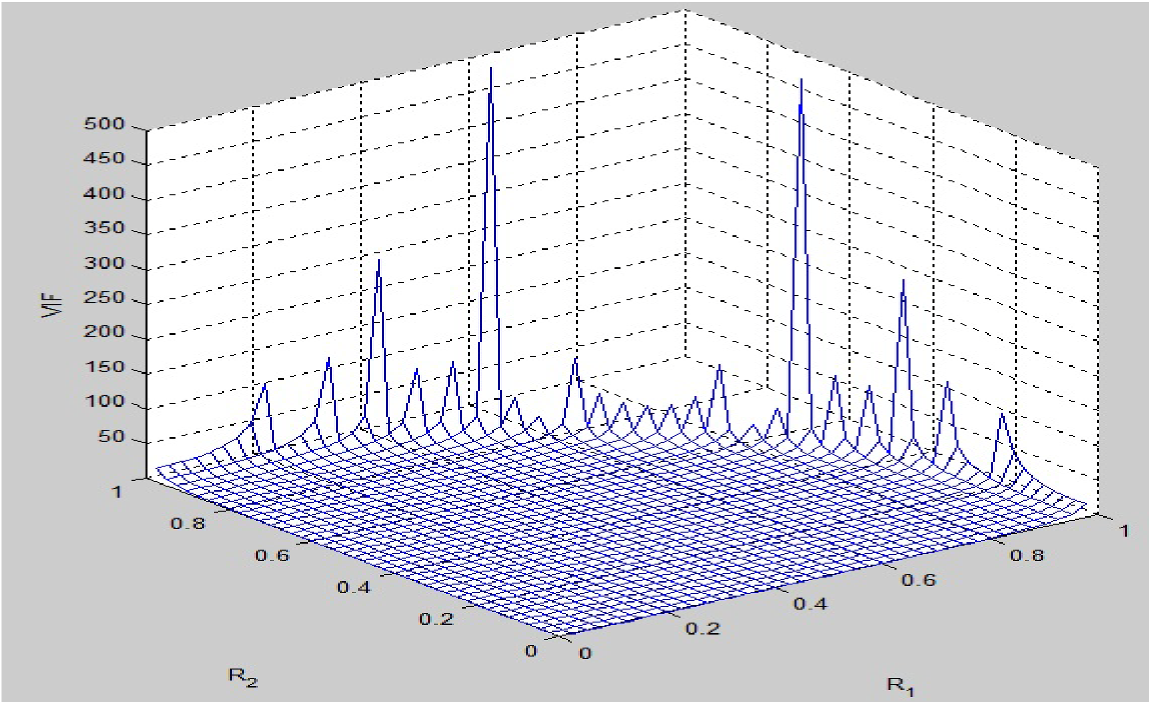



**Figure B-2. The Relationship Between VIF and Rs for Three Variables**

The points at which VIF values increase steeply are indicated as peaks (including small peaks) on the three-dimensional plot. Here a combination of values of $R_1$ and $R_2$ in the range of .6 to .8 lead to VIF values that are suggestive of collinearity for a threshold level of 3.3. For example, if $R_1$ and $R_2$ are both equal to .625, the corresponding VIF will be 4.57.

As blocks in an SEM model become more complex from a structural perspective, with more predictors pointing at the same criterion, the absolute value of correlations that can lead to significant lateral collinearity goes progressively down.

Analogously, as SEM models become more complex from a structural perspective, with more variables in them, the absolute value of correlations that can lead to significant full collinearity goes progressively down. That is, even if not in the same block, variables may still be redundant and cause interpretation problems when correlations are relatively low.

One key implication from this discussion is that not only is collinearity different from correlation, but also collinearity cannot be reliably inferred from correlation values alone except for very simple models. That is, in most cases, for collinearity to be reliably tested in variance-based SEM, VIF values must be calculated and compared against thresholds. Calculating correlations among latent variables and comparing those against thresholds is not sufficient to establish collinearity.

## Appendix C: Measurement Instrument (With Collinearity)

A Likert-type scale (0 = "Strongly Disagree" to 10 = "Strongly Agree") was used for each of the construct measurement indicators listed below. All constructs were measured reflectively.

### *Electronic Communication Media Variety (ECMV)*

This construct was measured by counting the number of tools reported as used "substantially" by each team from the following list. Here "substantially" means that the use of the tools was above the mid-point of their Likert-type use scales (i.e., above point 5; on a scale from 0 to 10).

ECM1. E-mail to fellow team members (1 to 1).
ECM2. E-mail to team distribution lists (1 to many).
ECM3. Team messaging boards or team discussion forums.
ECM4. Shared electronic files.
ECM5 Share electronic workspace to facilitate sharing information among team members.
ECM6. Electronic newsletters that covered project information.
ECM7. Auto routing of documents for team member and management approval.
ECM8. File transfer protocols (FTP) to attach documents to e-mails and Web pages.
ECM9. A Web page dedicated to this project.
ECM10. A Web page for this project that contained project specs, market research information, and test results.
ECM11. Voice messaging.
ECM12. Teleconferencing.
ECM13. Video conferencing
ECM14. Desktop video conferencing
ECM15. Attaching audio files to electronic documents.
ECM16. Attaching video files to electronic documents.

### *Team Project Management (Prjmgt)*

Prjmgt1. The team followed a clear plan -- a roadmap with measurable milestones.
Prjmgt2. There were adequate mechanisms to track the project's progress.
Prjmgt3. There were adequate mechanisms to track the project's costs.

### *Team Efficiency (Effic)*

Effic1. The product was launched within or under the original budget.
Effic2. The product came in at or below cost estimate for development.
Effic3. The product came in at or below cost estimate for production.
Effic4. The product was launched on or ahead of the original schedule developed at initial project go-ahead.
Effic5. Top management was pleased with the time it took us from specs to full commercialization.

### *Team Success in Terms Of Sales (SSucce)*

The product:

SSucce1. Met or exceeded volume expectations.
SSucce2. Met or exceeded sales dollar expectations.
SSucce3. Met or exceeded the 1st year number expected to be produced and commercialized.
SSucce4. Overall, met or exceeded sales expectations.

### *Team Success in Terms of Return On Investment (RSucce)*

The product:

RSucce1. Met or exceeded profit expectations.
RSucce2. Met or exceeded return on investment (ROI) expectations.
RSucce3. Met or exceeded overall senior management's expectations.

## Appendix D: Measurement Instrument (Without Collinearity)

Same as above, but with the two team success constructs, namely "Team success in terms of sales" and "Team success in terms of return on investment" merged into one construct: "Team success".

### *Team Success (Success)*

The product:

- Success1. Met or exceeded volume expectations.
- Success2. Met or exceeded sales dollar expectations.
- Success3. Met or exceeded the 1st year number expected to be produced and commercialized.
- Success4. Overall, met or exceeded sales expectations.
- Success5. Met or exceeded profit expectations.
- Success6. Met or exceeded return on investment (ROI) expectations.
- Success7. Met or exceeded overall senior management's expectations.

## Appendix E: Additional Factor Analysis Results

Below are additional results from the analysis. ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; SSucce: Team success in terms of sales; RSucce: Team success in terms of return on investment.

Table E-1 shows the unrotated loadings and cross-loadings from a confirmatory factor analysis (CFA). These loadings and cross-loadings are essentially the bivariate correlations between the indicators and latent variable scores. As mentioned before, loadings must be equal to or greater than .5 for convergent validity to be considered acceptable (Hair et al., 2009; Kline, 1998), which is the case here.

**Table E-1. Unrotated Indicator Loadings and Cross-Loadings (CFA)**

| | ECMV | PMngt | Effic | SSucce | RSucce |
|---|---|---|---|---|---|
| **ECMV** | (1.000) | 0.125 | 0.035 | 0.222 | 0.111 |
| **Prjmgt** | | | | | |
| **Prjmgt1** | 0.185 | (0.844) | 0.402 | 0.295 | 0.238 |
| **Prjmgt2** | 0.178 | (0.885) | 0.395 | 0.383 | 0.358 |
| **Prjmgt3** | 0.202 | (0.814) | 0.362 | 0.215 | 0.193 |
| **Effic** | | | | | |
| **Effic1** | 0.028 | 0.394 | (0.896) | 0.441 | 0.456 |
| **Effic2** | -0.026 | 0.402 | (0.884) | 0.359 | 0.388 |
| **Effic3** | 0.045 | 0.406 | (0.821) | 0.411 | 0.422 |
| **Effic4** | 0.061 | 0.306 | (0.813) | 0.412 | 0.379 |
| **Effic5** | 0.045 | 0.413 | (0.796) | 0.533 | 0.538 |
| **SSucce** | | | | | |
| **SSucce1** | 0.093 | 0.347 | 0.471 | (0.953) | 0.848 |
| **SSucce2** | 0.141 | 0.312 | 0.461 | (0.955) | 0.883 |
| **SSucce3** | 0.107 | 0.325 | 0.492 | (0.862) | 0.746 |
| **SSucce4** | 0.126 | 0.333 | 0.478 | (0.957) | 0.891 |
| **RSucce** | | | | | |
| **RSucce1** | 0.126 | 0.264 | 0.465 | 0.855 | (0.950) |
| **RSucce2** | 0.133 | 0.282 | 0.423 | 0.836 | (0.951) |
| **RSucce3** | 0.049 | 0.334 | 0.565 | 0.849 | (0.904) |

Note that many of the cross-loadings for SSucce and RSucce are greater than .5 as well; in fact, several are greater than .7. This is not necessarily an indication of collinearity, as the cross-loadings are expected to be high given the fact that they are unrotated and that there is a strong correlation between SSucce and RSucce. Nevertheless, these high cross-loadings can be seen also as red flags, much like the loadings greater than 1 present in the oblique-rotated loadings and cross-loadings table shown earlier.

Table E-2 shows the orthogonally rotated indicator and cross-loadings table, from an exploratory factor analysis (EFA), whereby 5 factors were extracted. In this case the loadings and cross-loadings were obtained after an orthogonal varimax rotation with Kaiser normalization. Note that the loadings for SSucce and RSucce were grouped together under factor 1, correctly. This would not be expected by a researcher who considered the associated indicators as belonging to different latent variables. Moreover, Effic was split across factors 2 and 4, which would also be unexpected, and arguably incorrect given the wording of the question statements. This unexpected grouping of indicators across extracted factors could be seen as a red flag as well.

**Table E-2. Orthogonally Rotated Indicator Loadings and Cross-Loadings (EFA)**

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| **ECMV** | 0.081 | -0.032 | 0.147 | 0.020 | (0.980) |
| **Prjmgt** | | | | | |
| **Prjmgt1** | 0.117 | 0.093 | (0.812) | 0.255 | 0.042 |
| **Prjmgt2** | 0.252 | 0.126 | (0.841) | 0.084 | 0.025 |
| **Prjmgt3** | 0.063 | 0.280 | (0.776) | -0.053 | 0.130 |
| **Effic** | | | | | |
| **Effic1** | 0.259 | (0.792) | 0.165 | 0.331 | -0.008 |
| **Effic2** | 0.176 | (0.879) | 0.189 | 0.220 | -0.056 |
| **Effic3** | 0.246 | (0.825) | 0.202 | 0.131 | 0.020 |
| **Effic4** | 0.206 | 0.412 | 0.089 | (0.801) | 0.055 |
| **Effic5** | 0.368 | 0.305 | 0.220 | (0.767) | -0.025 |
| **SSucce** | | | | | |
| **SSucce1** | (0.895) | 0.094 | 0.169 | 0.190 | -0.019 |
| **SSucce2** | (0.921) | 0.096 | 0.116 | 0.170 | 0.058 |
| **SSucce3** | (0.779) | 0.239 | 0.138 | 0.109 | 0.036 |
| **SSucce4** | (0.920) | 0.126 | 0.137 | 0.154 | 0.034 |
| **RSucce** | | | | | |
| **RSucce1** | (0.899) | 0.208 | 0.050 | 0.052 | 0.068 |
| **RSucce2** | (0.896) | 0.156 | 0.083 | 0.034 | 0.067 |
| **RSucce3** | (0.832) | 0.209 | 0.137 | 0.256 | -0.061 |

Note: Loadings and cross-loadings are after an orthogonal varimax rotation with Kaiser normalization.

Orthogonal rotation of loadings and cross-loadings is generally less frequently recommended than oblique rotation when latent variables are expected to be correlated (Ferguson, 1981; Thompson, 2004). This is the default expectation in variance-based SEM. Thus, tables with orthogonally rotated loadings and cross-loadings are not normally available as outputs in variance-based SEM software, but can be generated with generic statistical software tools (e.g., SPSS).

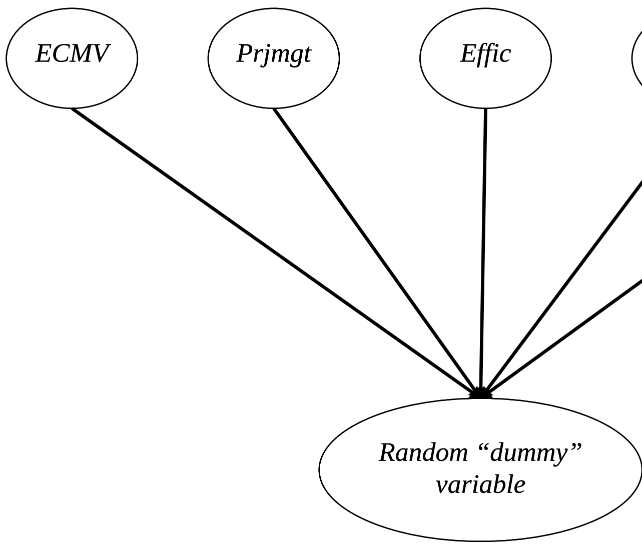
Factor analysis in the context of variance-based SEM is typically confirmatory and conducted in the context of SEM models with various hypothesized causal links. Causal links between latent variables are hypothesized and tested in variance-based SEM via the calculation of coefficients of association. If there were no correlations between latent variables, the coefficients of association would all be zero, and no hypotheses would be supported.

# Appendix F: Conducting a Full Collinearity Test with WarpPLS 2.0

The following steps can be used to conduct a full collinearity test with WarpPLS 2.0. (Version 3.0 of WarpPLS, which had not yet been released at the time of this writing, is expected to fully automate this test.)

First, add a new column to the original dataset, with random values. (This can be done with almost any spreadsheet software. With Excel, the “RAND” function is recommended.) Any range of random values may be employed; for example, random values varying from 0 to 1. This new column is essentially a new random “dummy” variable.

Second, create a model where all of the latent variables point at the new random dummy variable (see Figure F-1), which should be defined as a latent variable with a single indicator. This indicator refers to the column in the original dataset storing random values for the dummy variable.




Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; SSucce: Team success in terms of sales; RSucce: Team success in terms of return on investment.

**Figure F-1. Full Collinearity Test With WarpPLS 2.0**

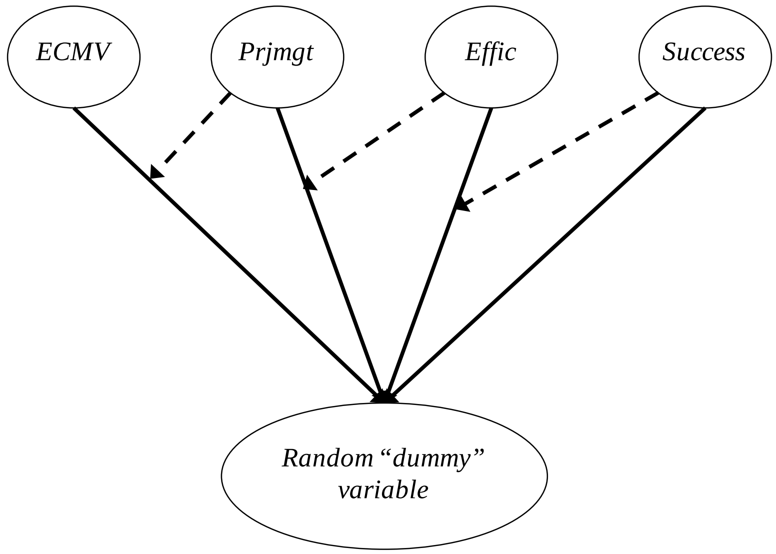
Third, run a SEM analysis using the “PLS Regression” algorithm. Forth, inspect the table with the VIFs, provided by the software under the menu option “View and save results”. There should be one VIF value for each of the latent variables.

If any VIF is equal to or greater than 3.3, then it can be concluded that collinearity is present in the model. Normally collinearity appears in pairs, suggesting that the two latent variables in question are actually measuring the same construct. In this case, a possible solution could be to combine the two latent variables into one, as in the illustrative example.

An alternative approach to identify the collinear latent variables that should be combined is to inspect the table with latent variable correlations, also provided by the software under the menu option “View and save results”. If two or more latent variables show VIFs that are equal to or greater than 3.3, and are significantly correlated, then they could be combined into one single latent variable. This alternative approach may be particularly useful when more than two latent variables show VIFs equal to or greater than 3.3. In this case, it may be difficult to identify the latent variables that are collinear with each other based on the inspection of the VIFs table alone.

# Appendix G: Moderating Effects and Collinearity

Three moderating effects were added to the model without collinearity in the illustrative example, where the model includes all latent variables configured in such a way as to allow for a full collinearity test. These moderating effects are represented through dashed arrows in Figure G-1.




Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; Success: Team success.

**Figure G-1. Moderating Effects Added to Explore Collinearity Inflation**

The full collinearity estimates are show on Table G-1. VIF values are shown for the original latent variables, as well as for the interaction latent variables. The latter are noted as latent variable products; for example, Success*Effic, in which case the moderating variable is Success, and the latent variable link being moderated is that between Effic and the dummy variable.

**Table G-1. Full Collinearity Estimates**

| ECMV | Success | Effic | Prjmgt | Success*Effic | Effic*Prjmgt | Prjmgt*ECMV |
|---|---|---|---|---|---|---|
| 1.076 | 1.434 | 1.762 | 1.478 | 1.297 | 1.279 | 1.008 |

Notes: ECMV: Electronic communication media variety; Prjmgt: Team project management; Effic: Team efficiency; Success: Team success.
Terms with a "*" symbol refer to moderating effects, where the variable listed before the "*" is the moderating variable. The VIFs shown are for all of the latent variables, including interaction variables; a "dummy" latent variable criterion was used. VIFs lower than 3.3 suggest no collinearity.

As it can be inferred from this table, the addition of moderating effects had little impact on the VIF values, with all of them eventually being lower than 2. The original VIF values, without the moderating effects, were also all lower than 2: ECMV=1.067; Success=1.420; Effic=1.585; and Prjmgt=1.351. As expected, all of them increased due to the inclusion of moderating effects (Echambadi & Hess, 2007), but only slightly. This rather limited increase in VIF values is likely due to the PLS regression algorithm, which tends to minimize collinearity among latent variables.

# About the Authors

**Ned KOCK** is Professor of Information Systems and Director of the Collaborative for International Technology Studies at Texas A&M International University. He holds degrees in electronics engineering (B.E.E.), computer science (M.S.), and management information systems (Ph.D.). Ned has authored and edited several books, including the bestselling Sage Publications book titled *Systems Analysis and Design Fundamentals: A Business Process Redesign Approach*. He has published his research in a number of high-impact journals including *Communications of the ACM*, *Decision Support Systems*, *European Journal of Information Systems*, *European Journal of Operational Research, IEEE Transactions* (various), *Information & Management*, *Information Systems Journal*, *Journal of the Association for Information Systems*, *MIS Quarterly*, and *Organization Science*. He is the Founding Editor-in-Chief of the *International Journal of e-Collaboration,* Associate Editor for information systems of the journal *IEEE Transactions on Professional Communication*, and Associate Editor of the *Journal of Systems and Information Technology*. His main research interests are biological and cultural influences on human-technology interaction, nonlinear structural equation modeling, information overload, electronic communication and collaboration, action research, ethical and legal issues in technology research and management, and business process improvement.

**Gary S. LYNN** is a Professor at Stevens Institute of Technology and an Affiliate Professor at Euromed Management. He started and built four companies – and sold three of them. Dr. Lynn was selected by *Business 2.0* magazine as one of the top ten management gurus in the world. He was also named twice (2003 and 2008), as one of the seven most prolific thought leaders in the field of Technology-Innovation Management by the International Association for the Management of Technology (IAMOT). Dr. Lynn was formerly Chief Innovation Officer and Senior Managing Director of Spencer Trask – a New York based venture capital company that placed $1.2 billion in 100 business over the past decade – where he worked with a variety of CEOs and board members across eight industries. He received a Bachelors of Mechanical Engineering from Vanderbilt University, a Masters of Management from the Kellogg School at Northwestern University, and his Ph.D. in marketing and new product development from Rensselaer Polytechnic Institute.