Operationalizing Multidimensional Constructs in Structural Equation Modeling: Recommendations for IS Research

Ryan T. Wright
University of Massachusetts Amherst, rtwright@admin.umass.edu

Damon E. Campbell
Millsaps College

Jason Bennett Thatcher
Clemson University, jason.b.thatcher@gmail.com

Nicholas Roberts
University of South Carolina Upstate

Operationalizing Multidimensional Constructs in Structural Equation Modeling: Recommendations for IS Research

Ryan T. Wright

University of Massachusetts Amherst

rtwright@admin.umass.edu

Damon E. Campbell

Millsaps College

Jason Bennett Thatcher

Clemson University

Nicholas Roberts

University of South Carolina Upstate

Abstract:

Although scholars have provided advice regarding how to conceptualize multidimensional constructs, less attention has been directed on how to evaluate structural equation models that include multidimensional constructs. Further, the extant information systems literature has provided little, and sometimes contradictory, direction on how to operationalize multidimensional constructs. This gap in how we approach multidimensional constructs merits attention because: (1) establishing construct validity is critical to testing theory and (2) recent advances in software enable testing models with multidimensional constructs more readily. Therefore, this tutorial (1) describes different forms of multidimensional constructs and (2) illustrates how to integrate superordinate and aggregate multidimensional constructs in structural equation models. In doing so, we offer guidelines and examples for how to conduct and evaluate research using multidimensional constructs.

Keywords: measurement, superordinate constructs, aggregate constructs, multidimensional construct, structural equation modeling, component-based SEM, covariance-based SEM

I. INTRODUCTION

A multidimensional construct is a single theoretical concept that is measured by several related constructs [Law et al., 1998]. This conceptualization of multidimensional constructs has been used to relay complex ideas about individuals' perception of trust toward information technology (IT) [McKnight et al., 2002], firms' IT-enabled capabilities [Zhu, 2004], and users' computer-self-efficacy [Marakas et al., 2007; Hardin et al., 2008; Marakas et al., 2008]. For example, to properly examine the effects of trust, McKnight et al. [2002] argue that one must understand the differing factors that compose trust. As a result, trust is modeled as a function of three factors: (1) benevolence—the extent to which a trustee is believed to want to do good on the other's behalf, (2) ability—the skills and competencies of the party, and (3) integrity—the perception that the trustee adheres to a set of norms. Using multidimensional constructs to operationalize such ideas is useful because they allow researchers to develop theories about relationships between complex multipart concepts within broader nomological networks [Law et al., 1998; Wong et al., 2008].

Recently, multidimensional constructs have received a great deal of attention within top information systems (IS) journals. Papers have suggested that researchers should "consider whether each construct, based on theory, is better represented as a first-order or as second-order construct" [Gefen et al., 2011, p. xi], offered in-depth guidance for how multidimensional constructs should be conceptualized [Polites et al., 2012], and critically assessed the implications of their use in empirical research [Shin and Kim, 2011]. This growing discourse on multidimensional constructs reflects the ease with which they may be modeled in recent releases of structural equation modeling (SEM) software such as AMOS, EQS, and SmartPLS. We anticipate that as theory using multidimensional constructs grows more pervasive, and tools more readily permit their inclusion in models, that many different forms of multidimensional constructs will appear with greater frequency in applied IS research.

While IS researchers have both suggested that multidimensional constructs are important and criticized their use, scant direction is available for scholars interested in the mechanics of how to test models that incorporate multidimensional constructs. To the best of our knowledge, there is a curious absence of "how-to" or "applied" examples of how to use SEM techniques to evaluate multidimensional constructs. Such guidance is important, because, while researchers may understand the theoretical concepts tied to modeling multidimensional constructs, they may lack the technical knowledge necessary to properly evaluate them. Moreover, absent practical guidance on how to operationalize multidimensional constructs, reviewers face challenges to evaluating models with multidimensional constructs that are theoretically and operationally consistent. Such practical barriers to multidimensional constructs' use in IS research include:

1. The misperceptions that multidimensional constructs are not supported by software, due to difficulties in modeling them in early versions of SEM software [Gefen and Straub, 2005; Gefen et al., 2011]

2. The absence of shared and consistent standards for assessing psychometric properties of such constructs [Edwards, 2001; Straub et al., 2004]

3. The challenges due to inadequate time, energy, or requisite knowledge to analyze and assess the research model (both measurement and structural)

To overcome these barriers to using multidimensional constructs, this tutorial's objective is to illustrate how to conceptualize and operationalize commonly used multidimensional constructs within the specific context of SEM. In doing so, we make these basic assumptions:

1. Researchers have appropriately defined multidimensional constructs based on theory [Polites et al., 2012]. This tutorial is meant as a companion piece to past publications on theorizing and conceptualizing about multidimensional constructs. For guidance on conceptualization, see [Law et al., 1998; Edwards and Bagozzi, 2000; Polites et al., 2012].

2. Researchers have taken care to adhere to well-established heuristics when selecting an SEM technique (see Gefen et al., 2011).

3. Measures used to operationalize the dimensions of a higher-order construct have been validated according to prescriptions found in the research methods literature (see MacKenzie et al., 2011; Shin and Kim, 2011).

We begin our tutorial by examining past IS research that has operationalized multidimensional constructs. Next, we describe commonly occurring types of multidimensional constructs (e.g., superordinate, aggregate, and other less common types). The next section provides an illustration of how to establish the validity of multidimensional constructs and how to include them in structural equation models. In doing so, we provide an example using cognitive absorption, an established multidimensional construct in the IS literature [Agarwal and Karahanna, 2000]. We also offer practical guidelines that help IS researchers to either conduct or evaluate research using multidimensional constructs. Finally, we provide a step-by-step guide on how to conduct multidimensional constructs in the appendices. Overall, this article complements prior IS research on multidimensional constructs [Kim et al., 2010; Polites et al., 2012] by providing scholars with guidance for how to implement common forms of multidimensional constructs in widely used SEM techniques.

II. USE OF MULTIDIMENSIONAL CONSTRUCTS IN INFORMATION SYSTEMS RESEARCH

Although many recent IS research papers have employed multidimensional constructs (see Table 1), there is a lack of consistency in the way in which multidimensional constructs have been empirically examined. Most organizational and behavioral IS research on multidimensional constructs draws on Law et al. [1998] or Edwards [2001] for guidance on conceptualization issues. Despite this shared foundation, there has been little convergence in the IS literature about appropriate ways to operationalize higher-order constructs [Kim et al., 2010; Polites et al., 2012]. For a complete review of how to theorize using multidimensional constructs, see Polites et al., 2012. Although many of these papers separately test first- and second-order models, recent advances in research methods enable researchers to test higher-order models that include all levels of multidimensional constructs (i.e., integrated, as opposed to separate, structural models). In the following section, we review differences in how some IS researchers have conceptualized and operationalized multidimensional constructs.

Differential Treatments of Construct Dimensionality

The IS literature contains several examples of conflict or disagreement among scholars about how multidimensional constructs should be conceptualized and operationalized. One example of such deliberation is the computer self-efficacy (CSE) literature. Originally, CSE was conceptualized as a unidimensional (i.e., single factor) construct with reflective measures [Compeau and Higgins, 1995]. More recently, CSE was conceived as a higher-order factor, but operationalized with formative indicators [Marakas et al., 2007]. This research spawned two related response publications that argued both sides of the reflective vs. formative item level debate for this multidimensional construct [Hardin et al., 2008; Marakas et al., 2008]. Interestingly, neither side of this specific exchange has operationalized CSE as a higher-order factor. Although these authors have not done so, other authors have explicitly argued that CSE is a higher-order construct that is "formed from the first-order factors" [Wang et al., 2008, p. 7] or hinted that a higher-order CSE construct exists. These papers reflect the view that "from a more distant perspective … each of the CSE percepts contribute to the formation of a perception of GCSE" [Marakas et al., 1998, p. 152]. Although conceptualized as multidimensional, much of the published research continues to operationalize CSE as a unidimensional construct. This lack of consistency between conceptualization and operationalization can create questions for researchers seeking to understand the implications of complex constructs in applied settings. For example, the following quote suggests a weak empirical linkage: "Four factor [model] found a better fit [i.e.,] beginning skills, file and s/w skills, advanced skills, & mainframe skills. [These] eight items showed r-squared, 0.50, and hinted of a multidimensional factor" [Marakas et al., 1998, p. 140]. To advance the CSE literature, scholars may need to revisit the conceptual framework that guides how to analyze and evaluate multidimensional constructs.

The Trust literature illustrates a second set of differences in how the IS literature theorizes about and operationalizes constructs. Since Trust's introduction to the IS literature, it has been conceived as a higher-order factor [McKnight et al., 2002]. While conceived as multidimensional, Trust has been evaluated in many different ways. For example, Klein states, "Additionally, trust beliefs constructs, [for the] provider and vendor, are specified as second-order formative constructs based on three reflective first-order dimensions [Jarvis et al., 2003], namely, ability, benevolence, and integrity" [Klein, 2006, p. 38]. Li et al. operationalized the same scale by, "the mean response for each dimension was calculated and then treated as a direct observation, thus the dimensions are listed in Table 2 instead of the individual items" [Li et al., 2008, p. 53]. Interestingly, Li et al. [2008] argue that, "there has been great variation in the operationalization and representation of these trust bases (e.g., one component vs. two components; second-order vs. first-order constructs; exclusion of one or more belief dimensions; and so on)" (p. 53). While Li et al.'s operationalization is not consistent with Klein's, they do sound a note of caution about the measurement of Trust, arguing that, "given the findings of our study, conclusions relating to the institutional base [of trust] when all dimensions are not measured, or the measurement representation is not consistent, may not be reliable" [Li et al., 2008, p. 53]. CSE and trust are just two of the many possible constructs that have been conceived and operationalized differently.

It is important to note that there are many reasons for differences in how researchers conceptualize and operationalize multidimensional constructs. For example, differences may exist because the focus of studies may differ. In one case, a construct could be correctly operationalized as a first-order factor, whereas in another study it may be correctly operationalized as a higher-order factor. Polites and colleagues summarize Mackenzie [2005] by arguing that "if a complex concept is the focus of the study, it is generally best to create a measurement model with all the critical conceptual distinctions, because it is important to thoroughly test and evaluate the construct. However, when such a construct is not central to the research or 'part of a complex system of relationships being investigated' (p. 715), then it is generally acceptable to substitute a simpler first-order construct, or a second-order construct with only a single measure per dimension" [Polites et al., 2012, p. 18]. Also, differences may exist because the research context differs. Burton-Jones and Straub [2006] suggest that constructs be operationalized with specific regard to the particular hypotheses being tested, and we should be wary of "omnibus" (general purpose) constructs. While retaining the conceptual meaning of the construct, they seem to imply that a construct's operationalization must be focused on the specific context, much more than has been the case historically in IS research. Finally, differences may exist because, as fields and methods evolve, the best tools and practices available to test sophisticated models may differ. For example, it is difficult to integrate first- and second-order models in omnibus tests if one is constrained to using regression. Consequently, rather than criticizing prior work, we believe it is important that IS researchers direct attention on how to (a) build on extant work using multidimensional constructs and (b) take care not to rely on simpler techniques that underutilize or lack the power of more advanced methods found in the literature.

While a recent IS paper has forwarded extensive guidance on how to conceptualize higher-order constructs [Polites et al., 2012], we would be remiss if we did not note at least two practical areas tied to multidimensional constructs in the IS literature that make a tutorial on the topic necessary. First, some researchers have offered first-order formative measures in their initial work on multidimensional constructs. For example, while Sun and Fang [2010] define IT *mindfulness* as being comprised of four dimensions, they suggest measuring each dimension with a single item and operationalizing the dimensions as a single construct. Such measurement is problematic, because it may oversimplify how we conceptually develop a construct and, therefore, might limit future understanding of how a higher-order construct operates within complex nomological networks [Polites et al., 2012]. Second, terms are often used inappropriately or inconsistently in research (e.g., a higher-order construct being referred to as reflective, when in fact it is superordinate). There is a great deal of research that appears to use the term *dimension* in different ways and represent this term as a first-order construct (see Bhattacherjee's [2001] description of Continuance, Fichman's [2001] conceptualization of IT-Related Innovation). For this reason, in the next section we will provide a standard set of terms that will define the types of multidimensional constructs.

These examples highlight the need for further understanding of multidimensional constructs and more resources regarding the application of that understanding (e.g., tutorials). Such understanding should be applied in conceptual development and guide our operationalization of new constructs. This view is consistent with classical and more recent research that has reemphasized the need for robust content analysis in construct development processes [Campbell and Fiske, 1959; Gefen et al., 2000; Straub et al., 2004; Gefen and Straub, 2005; Lewis et al., 2005; MacKenzie et al., 2011]. For example, Lewis et. al. [2005] and McKenzie et. al. [2011] highlight this need in their frameworks. In this work, MacKenzie et al. [2011] provide a ten-step overview of scale development which includes the major areas of conceptualization, development of measures, model specification, scale evaluation and refinement, validation, and norm development. Hence, our discussion turns to providing a concise guide to major forms of multidimensional constructs, as well as the operationalization and analysis of such constructs.

III. TYPES OF MULTIDIMENSIONAL CONSTRUCTS

Constructs are often conceptualized as multidimensional; yet, they are operationalized as unidimensional [Law et al., 1998]. Conceptually, a construct is multidimensional when a single theoretical concept refers to "a number of interrelated attributes or dimensions and exists in multidimensional domains" [Law et al., 1998, p. 741]. For instance, readiness to adopt electronic data interchange technology consists of interrelated dimensions such as financial resources, IT sophistication, and trading partner readiness that refer to distinct attributes [Chwelos et al., 2001]. Multidimensional constructs are distinguished from interrelated unidimensional constructs by one's ability to conceptualize the distinct dimensions under a "theoretically meaningful and parsimonious" overall abstraction. In the following pages, we provide examples of how the major types of multidimensional constructs (i.e., superordinate constructs and aggregate constructs) have been used in the IS literature.

When examining multidimensional constructs, it is important to distinguish between levels of abstraction. At a minimum, one must distinguish between the first level of abstraction, which relates distinct indicators to each dimension (first-order), and the second level of abstraction, which relates dimensions to the construct (second-order) [Edwards, 2001]. At the first-order level of abstraction, one may conceptualize the dimensions as reflective or formative (for a review of unidimensional reflective and formative constructs see Petter et al., 2007). Recent

literature provides strong evidence that formative indicators may cause stability problems for the construct [Kim et al., 2010; Edwards, 2011]; therefore, we caution the use of formative indicators without reviewing the issues and concerns. Because past literature has already illustrated, in detail, how to model first-order formative and reflective constructs (see Roberts and Thatcher, 2009), we focus on second-order constructs.

At the second-order level, multidimensional constructs are primarily distinguished by the relationship between the construct and its dimensions [Ones and Viswesvaran, 1996; Law and Wong, 1999; Edwards, 2001]. If the relationships flow from the construct to its dimensions, the construct is termed *superordinate* because it represents a general concept that occupies the domain of specific dimensions. If the relationships flow from the dimensions to the construct, the construct is aggregate because it combines or aggregates specific dimensions into a general concept. In either case, effectively measuring a multidimensional construct requires capturing each theoretical dimension.

It is important to use precise language to identify the relationship between a multidimensional construct and its dimensions. Not unlike first-order constructs, one often sees multidimensional constructs called *reflective* or *formative*. For example, Jarvis et al. identify four types of second-order constructs: (1) first-order reflective—second-order reflective, (2) first-order reflective—second-order formative, (3) first-order formative—second-order reflective, and (4) first-order formative—second-order formative [Jarvis et al., 2003]. However, conceptualizing multidimensional constructs as reflective or formative can be problematic, because at the second-order level the construct does not exist separately from its dimensions. Where reflective and formative imply causality, i.e., the overarching construct creates or is a function of its indicators, a multidimensional construct represents the association between a general concept and its dimensions [Law et al., 1998; Wong et al., 2008]. Thus, unlike a reflective first-order construct, one cannot drop a dimension of a superordinate second-order construct and retain its conceptual meaning. The relationship of causality remains important with multidimensional constructs. However, unlike a formative first-order construct, an aggregate second-order construct's value is conceptualized as either the additive or multiplicative value of its dimensions (i.e., all dimensions must be present to estimate its value) [Law et al., 1998; Wong et al., 2008]. Hence, the relationship between a multidimensional construct and its dimensions should not be confused with causality [MacCallum and Browne, 1993]; rather, it should be conceptualized as referring to the association between an overarching idea and its dimensions. In the following sections, we describe popular types of multidimensional constructs. Further, although the use of formative indicators is explicitly cautioned against [Kim et al., 2010], the use of formative relationships in the scope of construct associations, such as multidimensionality, is appropriate [Law et al., 1998; Wong et al., 2008; Kim et al., 2010]. Recent research does propose an alternative type of analysis to minimize these effects [Treiblmaier, 2011]. This technique is reviewed later in this article.

Other research has used the molar and molecular terminology to describe higher-order constructs [Chin and Gopal, 1995]. These terms have roots in psychology [Bagozzi, 1985, 1988], specifically in describing the construct attitude where, "a molar attitude is a global or macro presentation of a person's affective response to an object or actions" [Bagozzi, 1985]. A molecular approach to describe attitude is, "each belief represents a separate attitudinal dimension, which reflects an existing overall attitude" [Chin and Gopal, 1995]. There are several variations for the higher-order terminology throughout the extant literature. For the purposes of our illustrations on the conceptualization of higher-order factors, we will define the two type of higher-order constructs as superordinate and aggregate. This follows contemporary thought [Bollen and Lennox, 1991; Edwards, 2001, 2009].

Superordinate Construct

A superordinate construct is a general concept that is manifested in its dimensions. Not unlike indicators of a first-order reflective construct, a superordinate construct's dimensions are expected to covary [Bollen and Lennox, 1991]. Yet, whereas reflective measures are observed variables, the dimensions of a superordinate construct are themselves constructs that function as specific manifestations of a more general construct. This is an important distinction from a unidimensional reflective construct, where one may use indicators interchangeably to capture the construct's domain space. For example, IT relatedness is defined as the extent to which a multi-business firm uses common IT resources and common IT management processes across its business units [Tanriverdi, 2006]. Resource complementarity is a major aspect of IT relatedness. These resources are distinct, yet they are also interdependent. Moreover, they mutually support and reinforce each other. Following this, IT relatedness is conceptualized as a superordinate construct with four dimensions: IT Strategy Making, IT Vendor Management, IT HR Management, and IT Infrastructure. If one dimension is absent from IT relatedness, then it does not capture the overarching meaning of the superordinate construct (i.e., insufficient content validity). Hence, the domain space of IT relatedness may be represented as comprised of its dimensions (see Figure 1).
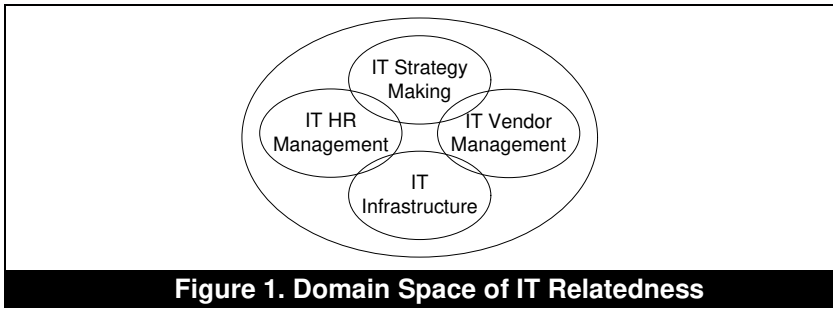
Figure 1. Domain Space of IT Relatedness

In some research, superordinate constructs have been operationalized by summing the factor scores of their first-order dimensions [Edwards, 2001]. However, this approach ignores measurement error and fails to capture differences in the relationships between the construct and its dimensions. To remedy these problems, methodologists initially recommended modeling the superordinate construct as a first-order factor (i.e., simply using dimensions as observed variables or indicators of the overarching construct) [Hanisch and Hulin, 1991]. However, this approach is problematic for two reasons: (1) it confounds random measurement error with dimension specificity, and (2) it disregards the relationships between each dimension and its measures. As a result, this approach introduces additional sources of error into estimating a structural model. Contemporary methodologists suggest modeling multidimensional constructs as second-order factor models. To do so, one models the superordinate construct as a second-order factor, its dimensions as first-order factors, and measures of the dimensions as observed variables [Hunter and Gerbing, 1982; Bagozzi and Edwards, 1998]. Figure 2 uses IT relatedness, a superordinate construct with four underlying dimensions, to illustrate the contemporary approach.
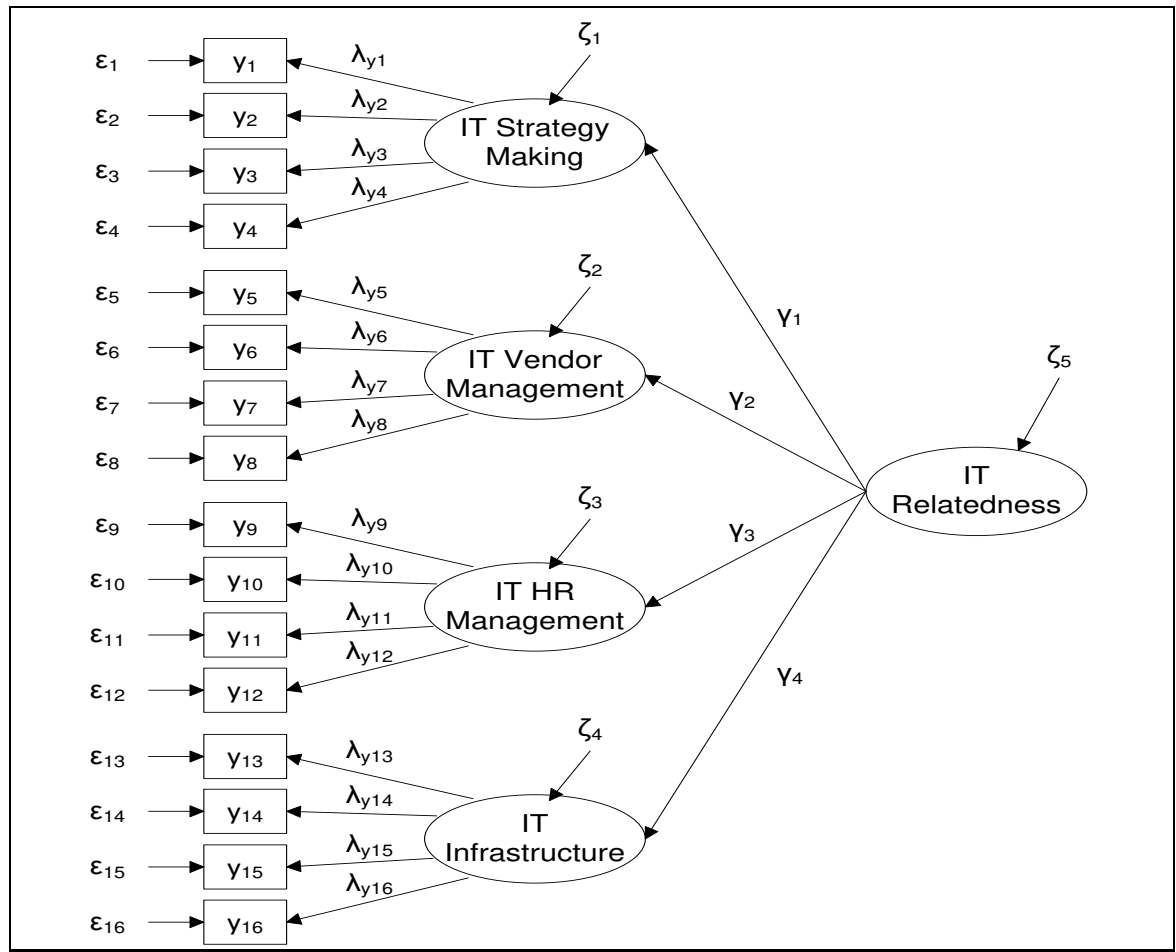

Figure 2. IT Relatedness as Superordinate Construct

Aggregate Construct

In contrast to a superordinate construct, an aggregate construct is a composite of its dimensions, meaning the dimensions combine to produce the construct. The dimensions of an aggregate construct are similar to formative

measures in that the dimensions do not necessarily covary [Bollen and Lennox, 1991]. Formative measures are observed variables; the dimensions of an aggregate construct are themselves constructs conceptualized as specific components of the general construct they collectively constitute. For example, supply chain process integration is defined as the degree to which a firm has integrated the flow of information, materials, and finances with its supply chain partners [Rai et al., 2006]. Following this, supply chain process integration is conceptualized as an aggregate construct with three dimensions: information flow integration, physical flow integration, and financial flow integration. The domain space of supply chain integration may look something like Figure 3.
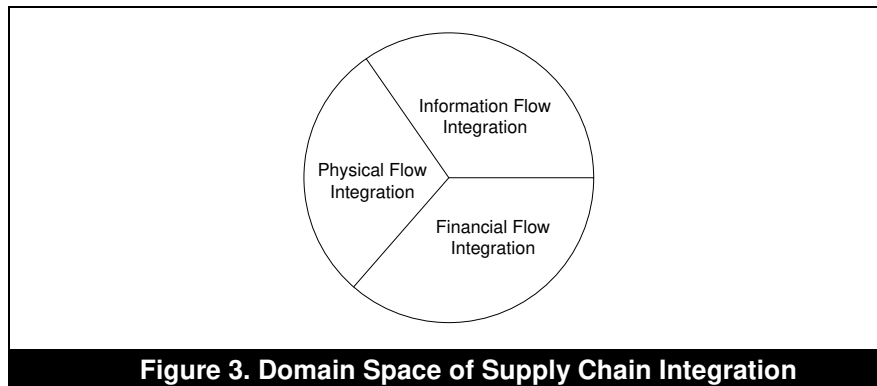

Figure 3. Domain Space of Supply Chain Integration

Aggregate constructs are usually operationalized by summing the scores of their first-order factors, such that the factors (i.e., dimensions) are assigned equal weight. In some cases, dimensions are assigned empirically derived weights obtained from principal components analysis or other types of exploratory factor analysis, which calculate weights based on correlations among the dimensions [Harman, 1976]. In other instances, dimension weights are determined by specifying the dimensions as formative indicators of the construct in a structural equation model [Bollen and Lennox, 1991]. To identify the structural model, the second-order construct must be specified as a direct or indirect cause of at least two observed variables [MacCallum and Browne, 1993]. Thus, the dimension weights are influenced not only by the correlations among the dimensions, but also by the relationships between the dimensions and the variables caused by the construct [Howell et al., 2007]. A residual term may be added to the model, such that the construct becomes a weighted composite of its dimensions plus random error and other unspecified variables [Bollen and Lennox, 1991]. Each of these approaches treats the dimensions of the aggregate construct as observed variables, thereby ignoring error in the dimension measures. This is done by specifying the dimensions as latent variables and their measures as manifest variables (i.e., a second-order factor model), as depicted in Figure 4 (an aggregate construct with three underlying dimensions).
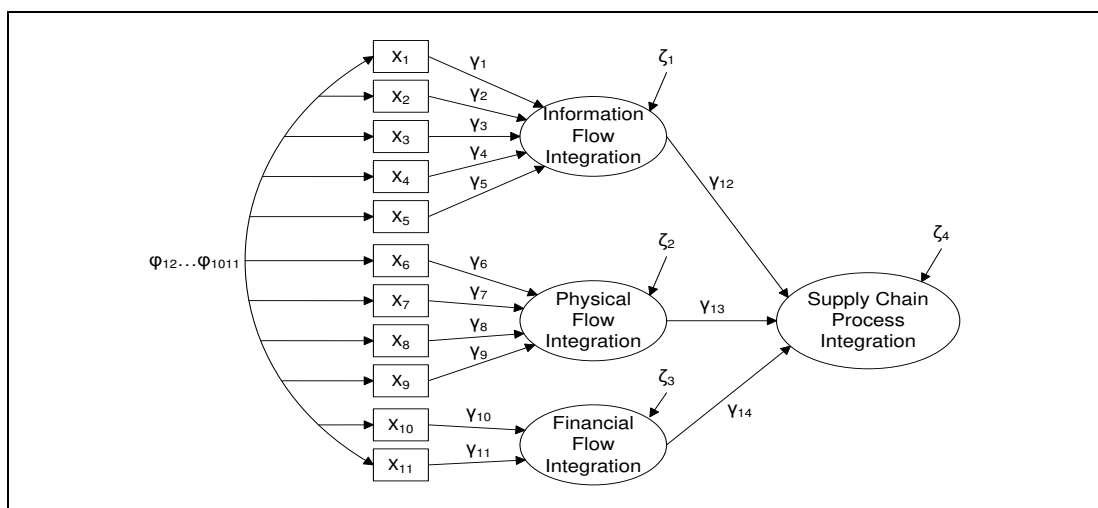

Figure 4. Supply Chain Process Integration as Aggregate Construct

Other Types of Multidimensional Constructs

Although most multidimensional constructs are either superordinate or aggregate [Law et al., 1998; Edwards, 2001], other types of multidimensional constructs exist. Some multidimensional constructs exist at the same level as their dimensions but are not defined as algebraic functions of their dimensions. This alternative approach to multidimensional conceptualization recognizes that multiple dimensions collectively provide insight into the global

construct, but are distinct enough to comprise individual constructs. In this approach, the multidimensional construct is modeled as a multivariate structural model where the dimensions are treated as separate yet related constructs. For example, Karahanna et al. [2006] employ a multivariate structural model to conceptualize and test compatibility in technology as an "overarching" multidimensional construct with distinct yet related dimensions (compatibility with preferred work style, existing work practices, prior experience, and values). This alternative approach acknowledges that not all multidimensional constructs have dimensions that would be positively correlated in all instances (i.e., superordinate construct), yet they may also not have dimensions that algebraically combine to form a multidimensional construct (i.e., aggregate construct).

Multidimensional constructs may also be derived from specific levels of their various dimensions. Also known as *profile constructs* [Becker and Billings, 1993], the dimensions of these multidimensional constructs cannot be combined algebraically. As a result, researchers usually identify various levels of their dimensions and interpret the construct by profiling the levels [Law et al., 1998]. For example, organizational environment has been conceptualized as a two-dimensional construct; specifically, the simple-complex and the static-dynamic dimensions [Duncan, 1972]. These two dimensions are combined to create four profiles of organizational environment. In turn, these profiles are theorized to have different impacts on various organizational structures and processes [Duncan, 1972].

Some multidimensional constructs combine features of superordinate and aggregate constructs. For example, a multidimensional construct may consist of both reflective and formative dimensions, similar to multiple indicator / multiple cause models in structural equation modeling [Joreskog and Goldberger, 1975]. Other multidimensional constructs have nonlinear relationships with their dimensions. For example, business–IT alignment has been defined as the absolute or squared difference between business strategy and IT strategy constructs [Chan et al., 1997]. While theoretically possible, these constructs appear infrequently in all literatures because of issues related to identifying the model or practical issues—i.e., statistical tools do not readily permit running such models [Diamantopoulos and Winklhofer, 2001; Jarvis et al., 2003; Wetzels et al., 2009]. For a complete review of these types of constructs, see Jarvis et al. [2003] and Diamantopoulos et al. [2008]. As a result, we focus on superordinate and aggregate constructs because they are prevalent in IS research and "provide a foundation for understanding other multidimensional constructs that relate to their dimensions in more complex ways" [Edwards, 2001, p. 148]. Table 1 presents a representative sample of IS studies that have conceptualized different forms of multidimensional constructs.

Table 1: Illustrative Multidimensional Constructs in IS Research			
Construct	Construct Type	Dimensions	Reference
Cognitive Absorption	Superordinate	• Temporal Dissociation • Focused Immersion • Heightened Enjoyment • Control • Curiosity	Agarwal and Karahanna, 2000
E-Commerce Capability	Superordinate	• Information • Transaction • Customization • Back-end Integration	Zhu, 2004
IT Relatedness	Superordinate	• IT Strategy Making • IT Vendor Management • IT Human Resource Management • IT Infrastructure	Tanriverdi, 2006
Knowledge Process Capability	Aggregate	• Acquisition • Conversion • Application • Protection	Gold et al., 2001
Mimetic Pressures	Aggregate	• Extent of Adoption Among Competitors • Perceived Success of Competitor Adopters	Teo et al., 2003
Supply Chain Process Integration Capability	Aggregate	• Information Flow Integration • Physical Flow Integration • Financial Flow Integration	Rai et al., 2006

IV. GUIDELINES FOR SPECIFYING AND ANALYZING MULTIDIMENSIONAL CONSTRUCTS

Tables 2 and 3 provide summaries of the process to follow when running analysis using covariance-based and component-based approaches to estimate models incorporating multidimensional constructs. For testing validity of models Chin suggests, "Tests of validity for a second order model should, by analogy, follow the same process that is used to examine the validity of first order models" [Chin, 2010]. To this end, Wetzels et al. [2009] provide a clear path for reflective indicators in determining discriminant and convergent validity for higher order constructs. To test for validity in formative indicators (see Roberts and Thatcher, 2009), who provide a three-step guideline. The steps for model estimation below assume the use of Chin [2010], Wetzels et al. [2009], or Roberts and Thatcher [2009] to determine that the test for discriminant and convergent validity of the higher order constructs with either formative or reflective indicators.

There are two methods for specifying higher-order constructs in PLS. One is the block method, where first-order variables are constructed. Then the second-order variable can be constructed by also relating the same items in the underlying first-order items. This method was based on the work of Wold [Lohmöller, 1989] and is outlined by Wetzels et al. [2009] in detail. "This procedure works best with equal number of indicators for each construct" [Chin 2010, p. 665]. We present an alternative method for operationalizing high-order factors in SEM that can be used generally for a variety of situations in PLS (e.g., different number of indicators) and in covariance-based SEM. We offer a step-by-step tutorial using screenshots from both SmartPLS and EQS in the Appendices. Also, we have made the data for this tutorial available at www.usf-research.org/CAIS-Wright.

Table 2: Process Steps for Covariance-Based Model Estimation				
Step 1	Step 2	Step 3	Step 4	Step 5
Run Model 1: First-order Factor Model	Run Model 2: Freely Correlated first-order Factors	Run Model 3: Tests of Discriminant Validity	(a) Run Model 4: Parallel Model (b) Run Model 5: Tau Equivalent Model (c) Run Model 6: Congeneric Model	Run Full Structural Model
Evaluate Fit Statistics: Fit should be poor	(a) Evaluate Fit Statistics: Improved Fit over Model 1 supports dimensionality (b) Evaluate Factor Loadings: Significant loadings support convergent validity	(a) Run two freely-correlated factors then constrain the correlation (b) Evaluate Fit Statistics: Significant X^2 change supports discriminant validity (c) Repeat for each pair of first-order factors	Compare Models 4, 5, and 6 to select the best fitting model.	

Table 3: Process Steps for Component-Based Model Estimation			
(1) Run first-order Measurement Model	(2) Evaluate Reliability using Internal Composite Reliability	(3) Evaluate Convergent Validity using Average Variance Extracted	(4) Evaluate Discriminant Validity using Construct Correlations and Item Loadings
(5) Create a new data file with the latent variable scores	(6) Construct second-order factor with the latent variable scores as indicators	(7) Run Full Structural Model	(8) Evaluate Structural Model Results

Note that these process maps focus on the steps of model specification, estimation, and analysis in scale development. These maps assume that the steps of conceptualization, item generation, content validity, and scale purification have already been conducted [Gefen et al., 2000, 2011; MacKenzie et al., 2011]. We highly recommend Appendix A in MacKenzie et al. [2011] for recommendations on scale purification and refinement in the case of multidimensional scales. Before illustrating the steps proposed in Tables 2 and 3 in an example, we believe it would

be useful for researchers to consider the following guidelines as they approach data analysis. These guidelines are focused on second-order constructs, not levels of abstraction higher. By doing so, problems in reporting or estimating models incorporating multidimensional constructs may be avoided.

General Guidelines

The following guidelines represent suggestions one should consider when using either covariance- or component–based SEM techniques.

General Guideline 1: Researchers should take care to follow generally accepted procedures for scale development and validation.

There have been and undoubtedly will continue to be research in the area of psychometric evaluation of scales. Here we highlight a few of these accepted practices as pertains to multidimensional constructs.

First, researchers must outline the conceptualization and construct definition clearly [Gefen and Straub, 2005; Gefen et al., 2011]. This entails identifying all relevant dimensions, aggregate vs. superordinate conceptualization at both the first and second-order, and relevant relationships and distinctions with other constructs. Poorly conceptualized constructs or ill-defined constructs will always lead to problems of operationalization and specification.

Second, one should avoid under-identifying a model with one or more multidimensional constructs. Since they have the same basic structure, aggregate cause models and superordinate effect models raise similar identification issues [Edwards, 2001]. For both types of models, the multidimensional construct must have paths leading to at least two endogenous variables [MacCallum and Browne, 1993]. This condition is satisfied if a superordinate effect has at least two dimensions or an aggregate cause has at least two effects. This is an application of a procedure called a MIMIC (multiple indicators, multiple causes) model structure for multidimensional constructs that has been widely proposed (see MacKenzie et al., 2011) for details on first-order operationalization).

Third, researchers should use caution when modeling aggregate constructs. Research has shown instability in model estimation depending on endogenous variables used in first-order formative constructs [Kim et al., 2010]. Similar instability is expected with aggregate constructs. Therefore, researchers should use caution in their claims when endogenous variables are needed to estimate downstream model characteristics.

Finally, we would like to highlight that while theory should drive the decision to model a construct as multidimensional, covariance-based SEM analysis should include multiple criterion that compares first and second-order models. In our example application, we identify five criterion employed in prior IS research that help to evaluate whether a construct is multidimensional. With the exception of the goodness of fit, the criteria related to construct correlations, second-order loadings, target T-statistics, and structural relationships constitute a useful set of heuristics for authors and reviewers to employ when assessing the appropriateness of modeling multidimensional constructs.

General Guideline 2: When modeling aggregate constructs, researchers should be aware of the strengths and weaknesses of various methods of analyses.

When using covariance-based SEM incorporating an aggregate construct as a cause in a causal model, one must take into account model identification issues [Kim et al., 2010]. Specifically, the aggregate construct (modeled as a cause) must have paths leading to at least two endogenous variables [MacCallum and Browne, 1993]. However, recent research has provided an alternative to the multiple indicator multiple causes (MIMIC) method to analyzing formative and aggregate constructs. This method divides indicators into separate composites and models a formative dimension as an aggregate construct with reflective first-order factors [Treiblmaier, 2011]. This removes the identity problem associated with the MIMIC method. MIMIC (multiple indicators and multiple causes analysis) is a less common method of examining invariance in multiple groups [Brown, 2006]. To estimate a model including aggregate constructs in component-based SEM, researchers should model the relationship arrows as going from the first-order dimensions to the second-order construct (i.e., in a manner similar to modeling formative constructs). Understanding which of these analyses is most appropriate for the circumstances is the researcher's responsibility.

General Guideline 3: When possible, researchers should assess the validity of multidimensional constructs using theorized antecedents or consequences in the nomological network.

This guideline is most applicable in the pretesting stages of scale purification and refinement. MacKenzie et al. [2011] illustrate four types of relationships multidimensional constructs which can be used to guide validity (see pp. 322–323). In sum, by testing the direct relationship of the dimensions with their antecedents or consequences, depending on the type of relationship, the relevance of the dimensions can be inferred.

Covariance-Based SEM Guidelines

The following guidelines represent suggestions when executing covariance-based structural equation models.

Covariance-based SEM Guideline 1: Researchers should set a scale for the multidimensional construct by fixing its variance to 1.0.

To conduct statistical tests involving the multidimensional construct, one must obtain standard errors for paths leading to and from the construct, and these standard errors cannot be calculated for fixed paths [Bollen, 1989]. Hence, it is preferable to set the scale of the multidimensional construct by fixing its variance [Edwards, 2001]. This avoids setting the metric of the construct to a single item, which has been shown to create problems of validity [Kim et al., 2010].

Covariance-based SEM Guideline 2: Researchers should assess model fit in conjunction with comparisons of alternative models.

Although this guideline is not specific to multidimensional constructs, its relevance is accentuated in these cases. Model fit should be assessed using indices recommended in the SEM literature, such as the comparative fit index (CFI) and the root mean square error of approximation (RMSEA) [Bentler, 1990; Boomsma, 2000; Gefen et al., 2000]. Assessments of model fit should be supplemented by comparisons with alternative models [Anderson and Gerbing, 1988]. For a superordinate construct, the parallel, tau equivalent, and congeneric models may be compared with one another. For an aggregate construct, models with equal or principal component dimension loadings may be compared with models that freely estimate these loadings.

Component-based SEM Guideline: Researchers should assess the first-order measurement model separately from the second-order structural model.

When reporting the results of a superordinate multidimensional construct, researchers should take care to follow guidelines for establishing convergent and discriminant validity identified in Straub et al. [2004]. In assessing an aggregate multidimensional construct, researchers should take care to follow guidelines offered by Roberts and Thatcher [2009]. When assessing the second-order structural model, researchers should adhere to heuristics provided by Gefen et al. [2000].

V. AN APPLICATION OF THE GUIDELINES FOR EVALUATING MULTIDIMENSIONAL CONSTRUCTS

In this section, we step through two different scenarios of how to empirically test multidimensional constructs within an SEM model based on the guidelines provided above. We use cognitive absorption (CA), a superordinate multidimensional construct, to illustrate how to execute a model utilizing EQS, a covariance-based SEM (CB-SEM) software application. Next, we again use CA but this time utilizing SmartPLS, a component-based software application. In order to choose the appropriate technique, review Gefen et al., 2000, 2011. First, we will explain the details of the research model, which is common for both techniques.

The Referent Study

CA refers to a state of deep involvement with software that influences two critical beliefs about technology use: perceived usefulness and perceived ease of use [Agarwal and Karahanna, 2000]. CA is comprised of five dimensions: temporal dissociation, focused immersion, heightened enjoyment, control, and curiosity. Figure 5 depicts our research model. In the following section, we describe our research design, study context, and construct measures. This is followed by data analysis with both covariance-based and component-based SEM for a superordinate construct. Finally, we compare the results of our analyses, propose guidelines in the use of these analyses, and elaborate on the modeling of aggregate constructs.

We used a research design similar to that of Agarwal and Karahanna [2000] to estimate and evalute the original CA model. We collected data from student subjects enrolled at a large state university. Given the nature of the sample, we chose Internet Applications as the target technology. Internet Applications consist of the World Wide Web, E-mail, and Instant Messenger. Students were instructed to respond to the survey as candidly as possible, that there were no right or wrong answers, and that we were primarily interested in their use of Internet Applications.

A total of 318 surveys were returned. Approximately 10 percent of our data was missing. We performed Little's MCAR test [Little and Rubin, 1987] and found that these values were missing completely at random ($p > .05$). This test suggested that the missing values were not based on a hidden systematic pattern. Thus, any imputation method
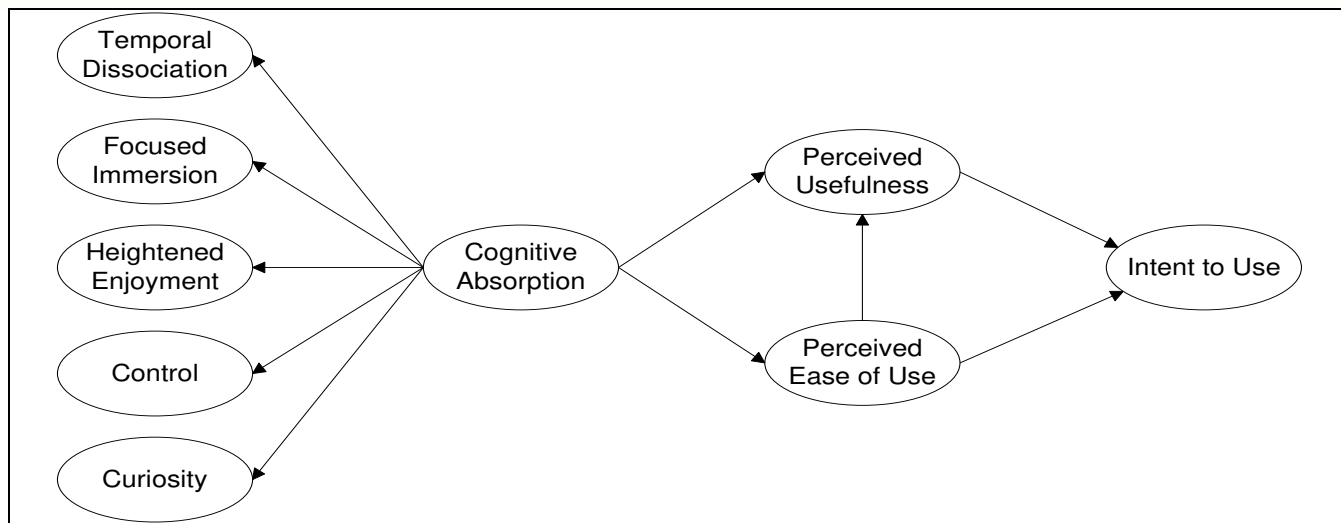
Figure 5. Research Model

could be applied to replace them [Hair et al., 1998]. We imputed missing data using the direct maximum likelihood imputation method in EQS 6.1 [Byrne, 2006]. Direct ML imputation methods have been found to be more favorable and robust than traditional methods of handling missing data, such as listwise or pairwise deletion [Allison, 2003]. Our final data set included 318 respondents.

Construct measures were adapted from previously validated multi-item scales (see Appendix D). Behavioral intention to use Internet Applications was measured using a three-item scale adapted from Davis et al. [1989]. Indicators for perceived usefulness and perceived ease of use were based on Davis [1989]. Finally, cognitive absorption was measured using the full twenty-item scale adapted from Agarwal and Karahanna [2000].

Data Analysis Using Covariance-Based SEM

We used EQS 6.1 to analyze our data with covariance-based SEM. The step-by-step instructions for utilizing EQS can be found in Appendix A. The EQS code used in this example can be found in Appendix B. To determine support that CA is a multidimensional construct, we statistically compare the fit of two distinct conceptualizations of the construct. The first model depicts CA as a single first-order factor. The second model depicts CA as a multidimensional second-order construct.

Next we execute Model 1 and Model 2 to address General Guideline 1: Researchers should take care to follow generally accepted procedures for scale development and validation.

Model 1: First-Order Factor Model

Our first measurement model tests for the multidimensionality of cognitive absorption. Specifically, we hypothesize that a unidimensional first-order factor model accounts for the variance among all twenty indicators (see Figure 6).To assign a measurement scale to each factor, we must fix a single indicator path for each factor to be 1.0 [Kline, 2005]. We note that a traditional assumption in covariance-based SEM is that the relationship between the observed variables and their constructs and between one construct and another is linear [Gefen et al., 2000; Qureshi and Compeau, 2009]. Additionally, EQS 6.1 provides statistics (e.g., model fit, parameter estimates) which are robust to non-normality [Byrne, 2006]. Please note that WarpPLS is a component-based approach that provides estimates using the assumption that constructs are nonlinearly related. Bentler [2005] suggests that kurtosis (absolute) values greater than 5.00 are indicative of data that are non-normally distributed. The normalized estimate in our data (64.62) exceeds the recommended cutoff values, thereby suggesting that the data is not normally distributed. Therefore, we use the Satorra-Bentler scaled χ2 statistic [Satorra and Bentler, 1988], as well as robust fit estimates used in prior IS research [Swanson and Dans, 2000], which are reported to be highly reliable for estimation purposes [Hu et al., 1992].

Our confirmatory factor analysis provides evidence of poor model fit (χ^2 = 1738.32, d.f. = 170; CFI = 0.55; RMSEA = 0.171). The poor model fit suggests that the indicators do not load on a single factor. We compare these model fit indices with a multidimensional model in the next section.

Model 2: Dimensionality and Convergent Validity

In the second model, we respecify the model to represent first-order factors for each dimension of cognitive absorption. We aim to provide evidence of multidimensionality and convergent validity. Specifically, in this model we hypothesize that the twenty indicators indicate five freely correlated first-order factors (see Figure 6). Comparison of Model 1 (χ^2 = 1738.32, d.f. = 170; CFI = 0.55; RMSEA = 0.171) and Model 2 (χ^2 = 418.06, d.f. = 160; CFI = 0.93; RMSEA = 0.071) shows that Model 2 is a better-fitting model (lower chi-square for the same degrees of freedom and improved fit indices), showing that a multidimensional model comprised of five freely correlated first-order factors is superior to a unidimensional first-order factor model. Thus, we obtain support for the multidimensionality of cognitive absorption. Furthermore, standardized factor loadings of indicators on their respective factors are all highly significant ($p < 0.001$), providing support for convergent validity. We recognize that the standardized loadings are below a widely accepted threshold of .70. Considering the use of established measures, and the result that these loadings remain significant [Tippins and Sohi, 2003], we continued the analysis to demonstrate the proposed method for modeling multidimensional constructs.
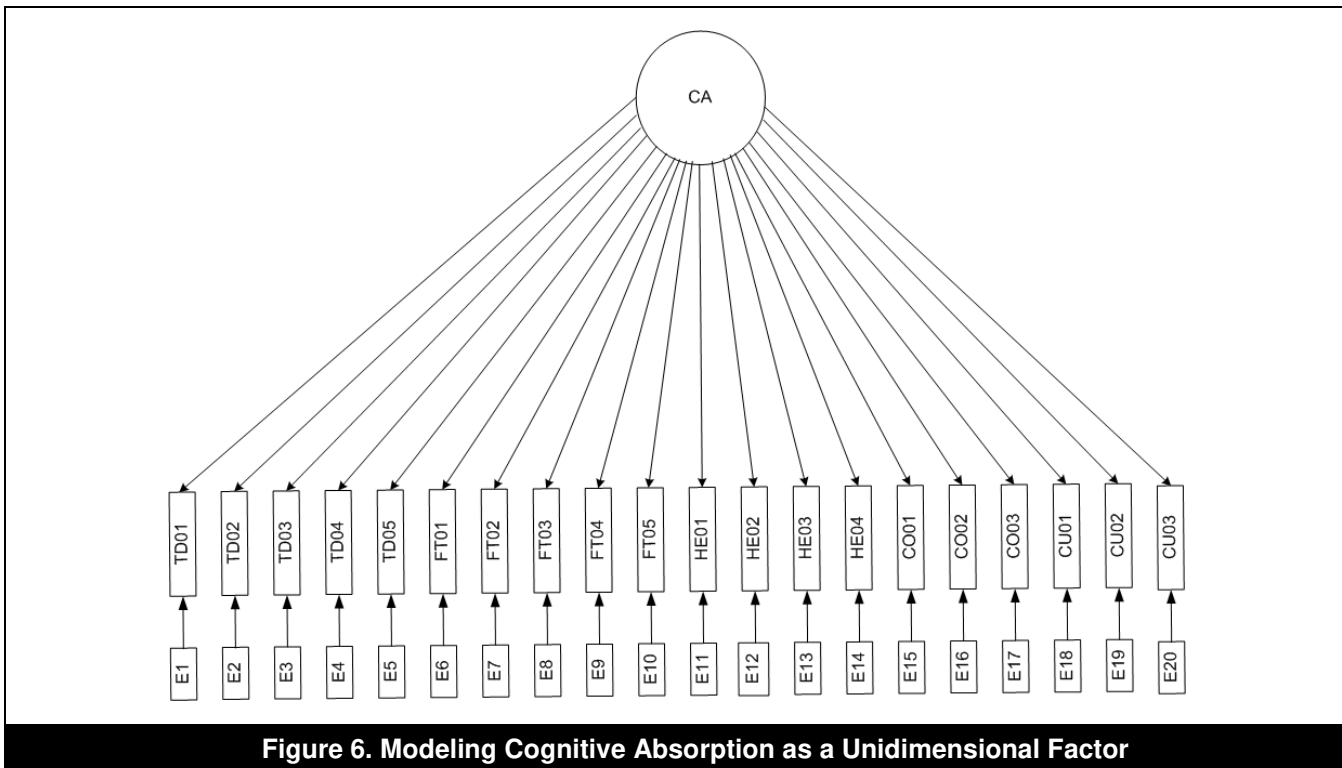
Figure 6. Modeling Cognitive Absorption as a Unidimensional Factor

Model 3 addresses Covariance-based SEM Guideline 1: Researchers should set a scale for the multidimensional construct by fixing its variance to 1.0.

Model 3: Discriminant Validity

In the third model, we establish that each first-order factor is discriminant from the other first-order factors. We do this by creating a model with just two first-order factors. First, we run a confirmatory factor analysis (CFA) with a pair of factors allowed to freely covary. Next, we constrain the covariance to 1.0. We then evaluate the change in χ^2 across the models. If constraining the covariance to 1.0 significantly hampers the χ2 statistic, then we have evidence of discriminant validity [Venkatraman, 1989]. In other words, the two first-order factors represent two distinctly different factors and do not perfectly covary. However, if constraining the covariance does not significantly hamper model fit, then the two first-order factors may not be significantly different. To provide evidence of discriminant validity among all factors, we repeat this process for each pair of factors. The results are summarized in Table 4. In order to move forward, we will assume that the scales have been vetted in accordance to General Guideline 1: Researchers should assess the validity of multidimensional constructs using theorized antecedents or consequences in the nomological network.

Then, the final two models enable us to follow Covariance-based SEM Guideline 2: Researchers should assess model fit in conjunction with comparisons of alternative models.

Model 4: Parallel Model

The remainder of our covariance-based models includes a second-order factor. Edwards [2001] suggests that three alternative models (parallel, tau equivalent, and congeneric) should be tested when modeling a superordinate second-order factor. Table 5 describes and defines these measurement models and guidelines for their assessment. Using the three alternative models is common in psychology [Kline, 2005; Brown, 2006] when one needs to identify the path model (parallel) and measure internal consistency (tau-equivalent) and reliability (congeneric) in longitudinal and higher-order models. By starting with a model that restricts loadings and variances, we are able to determine the item scores given that the true score is the same for all items. A parallel model is the most restrictive; specifically, the dimensions are treated as parallel, meaning they have equal loadings and equal residual variances. Parallel models are used to identify the SEM path diagrams [Graham, 2006]. A tau equivalent model is less restrictive in that it models dimensions with equal loadings yet different residual variances. The tau equivalent measurement model is commonly used to measure internal consistency. Finally, the least restrictive model treats the dimensions as congeneric, meaning their loadings and residual variances are allowed to freely vary. This model is most generally used for reliability estimates [Graham, 2006].
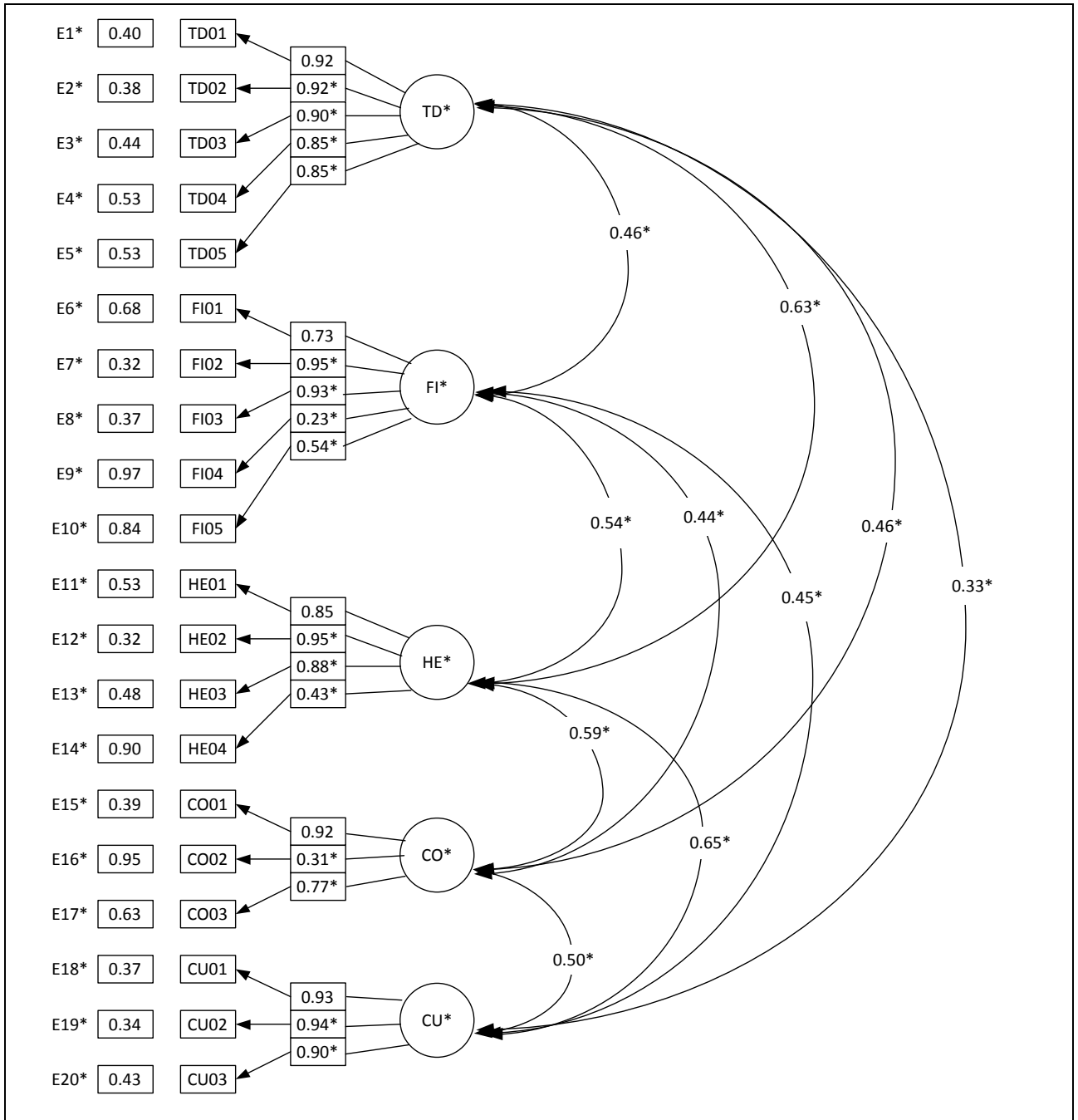
Figure 7. Standardized Solution for Model 2

Table 4: Assessment of Discriminant Validity*			
Dimensions	Unconstrained Model χ^2 (df)	Constrained Model χ^2 (df)	Δ χ^{2*}
Temporal Dissociation with			
Focused Immersion	286.37 (34)	305.32 (35)	18.95
Heightened Enjoyment	272.52 (26)	279.38 (27)	6.86
Control	219.72 (19)	233.05 (20)	13.33
Curiosity	222.28 (19)	253.74 (20)	31.46
Perceived Ease of Use	238.05 (26)	260.07 (27)	22.02
Perceived Usefulness	217.98 (26)	261.62 (27)	43.64
Intention to Use	243.49 (19)	253.91 (20)	10.42
Focused Immersion with			
Heightened Enjoyment	118.24 (26)	141.76 (27)	23.52
Control	100.93 (19)	124.63 (20)	23.70
Curiosity	85.10 (19)	112.68 (21)	27.58
Perceived Ease of Use	71.93 (26)	106.79 (27)	34.86
Perceived Usefulness	81.09 (26)	109.68 (27)	28.59
Intention to Use	79.43 (19)	124.20 (20)	44.77
Heightened Enjoyment with			
Control	129.22 (13)	141.84 (14)	12.62
Curiosity	28.79 (13)	40.12 (14)	11.33
Perceived Ease of Use	42.12 (19)	72.28 (20)	30.16
Perceived Usefulness	54.18 (19)	73.28 (20)	19.10
Intention to Use	43.16 (13)	69.34 (14)	26.18
Control with			
Curiosity	35.98 (8)	51.84 (9)	15.86
Perceived Ease of Use	38.20 (13)	45.54 (14)	7.34
Perceived Usefulness	38.29 (13)	48.11 (14)	9.82
Intention to Use	27.91 (8)	42.23 (9)	14.32
Curiosity with			
Perceived Ease of Use	26.61 (13)	68.50 (14)	41.89
Perceived Usefulness	25.27 (13)	53.29 (14)	28.02
Intention to Use	5.80 (8)	57.13 (9)	51.33
Perceived Ease of Use with			
Perceived Usefulness	64.52 (19)	71.89 (20)	7.37
Intention to Use	26.13 (13)	44.26 (14)	18.13
Perceived Usefulness with			
Intention to Use	58.26 (13)	66.81 (14)	8.55
* All change in χ^2 are significant at p < .01			

We test the parallel model first. The parallel model is a superordinate model (see Figure 8) which constrains the factor loadings and residual variances to be equal. The parallel model suggests that each first-order factor equally represents the superordinate (second-order) construct, so that changes in the superordinate construct result in equal changes among all first-order dimensions [Edwards, 2001]. Also, the parallel model assumes that each first-order construct is of equal accuracy in representing the superordinate construct.

Figure 8 depicts our initial second-order model. Our confirmatory factor analysis provides evidence of acceptable model fit (χ^2 = 483.48, d.f. = 173; CFI = 0.91; RMSEA = 0.075, 90% C.I. = 0.067, 0.083). We compare results from the parallel model to the tau equivalent and congeneric models to understand the relative accuracy and equality of each first-order factor.

Model 5: Tau Equivalent

The tau equivalent model is less restrictive than the parallel model. The tau equivalent model constrains the factor loadings to be equal, but allows the residual variances to freely vary. This model suggests that the first-order factors represent the superordinate construct equally such that changes in the superordinate construct result in equal changes among first-order factors. However, since the residual variances are allowed to freely vary, the first-order factors represent the superordinate construct with varying levels of appropriateness. Our confirmatory factor analysis provides evidence of good model fit (χ^2 = 449.99, d.f. = 169; CFI = 0.92; RMSEA = 0.072, 90% C.I. = 0.064, 0.080). We compare these results to the parallel and congeneric models.

Table 5: Measurement Models		
Model	Description	Assessment
First-order Factor Model (Model 1)	The first-order factor is a baseline model, which suggests that the indicators represent a single factor.	If fit statistics are good, the construct may not be accurately modeled as multidimensional. If fit statistics are poor, the fit may improve when the construct is modeled as multidimensional.
Freely correlated first-order Factors Model (Model 2)	This model accounts for potential multidimensionality in the construct. Significant indicator loadings support convergent validity.	Poor fit may suggest little support for multidimensionality. Indicators that are not significant may not be converging on the factor.
Tests of Discriminant Validity (Model 3)	By comparing constrained and freely-correlated pairs of factors, this set of tests identifies whether factors are distinct from each other.	Significant χ^2 change supports discriminant validity. Non-significant χ^2 change suggests the two first-order factors may not be significantly distinct from each other.
Parallel Model (Model 4)	The parallel model assumes that the first-order dimensions are equal representations of the superordinate construct, and are also all equally reliable representations.	Poor fit suggests that the first-order dimensions may not be equal representations of the superordinate construct, may not be equally reliable representations, or may not be well-modeled as a superordinate construct.
Tau Equivalent Model (Model 5)	The tau equivalent model assumes that the first-order dimensions are equal representations of the superordinate construct, but are not all equally reliable representations: some dimensions are more accurate representations than others.	Poor fit suggests that the first-order dimensions may not be equal representations of the superordinate construct, or may not be well-modeled as a superordinate construct.
Congeneric Model (Model 6)	The congeneric model assumes that the first-order dimensions are not equal representations of the superordinate construct and are not equally reliable representations.	Poor fit suggests that the construct may not be well-modeled as a superordinate construct.

Model 6: Congeneric Model

The congeneric model is the same as the parallel and tau equivalent models with one exception: all constraints are removed. We simply build and run the superordinate model without any constraints imposed. Moreover, the congeneric model represents a standard second-order factor model [Rindskopf and Rose, 1988]. Our confirmatory factor analysis for the congeneric model provides evidence of good model fit ($\chi^2 = 434.77$, d.f. = 165; CFI = 0.92; RMSEA = 0.072, 90% C.I. = 0.064, 0.080). We compare model fit indices for the parallel, tau equivalent and congeneric models in Table 6.

The parallel, tau equivalent and congeneric models are nested models; thus, we can compare them using χ^2 difference tests. First, the difference between the parallel and tau equivalent model ($\Delta\chi^2 = 33.49$, d.f. = 4, p < .01) suggests that the first-order factors vary in quality as representations of the superordinate construct. Second, the difference between the tau equivalent and congeneric model ($\Delta\chi^2 = 15.22$, d.f. = 4, p < .01) suggests that the first-order factors are influenced in a differential manner by the superordinate construct. Therefore, we conclude that the congeneric model is the most accurate representation of the superordinate construct cognitive absorption.
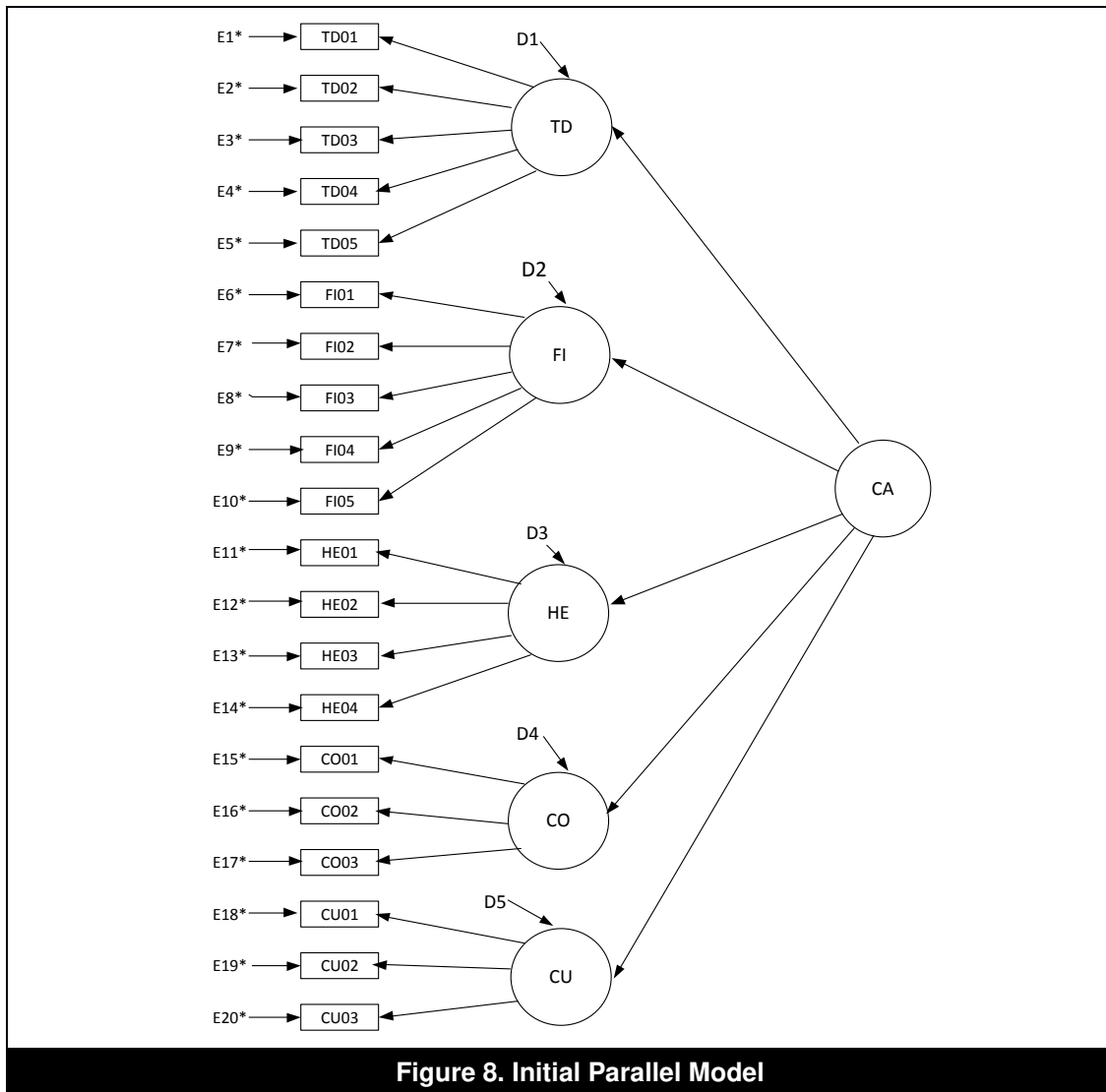
Figure 8. Initial Parallel Model

Table 6: Superordinate Models for Cognitive Absorption					
	X^2	d.f.	CFI	RMSEA	RMSEA 90% C.I.
Parallel Model	483.48	173	0.91	0.075	0.067, 0.083
Tau Equivalent Model	449.99	169	0.92	0.072	0.064, 0.080
Congeneric Model	434.77	165	0.92	0.072	0.064, 0.080

Structural Model

Having assessed the dimensionality, convergent validity, and discriminant validity of our superordinate construct, we can proceed to an analysis of the structural model that integrates measurement and structural relationships suggested by Agarwal and Karahanna [2000]. Figure 9 depicts our structural model.

Since the normalized estimate of Mardia's coefficient in our data (89.56) exceeds the recommended cutoff values, we assume that our data is not normally distributed. Therefore, we use the robust statistics, which are designed to be used for non-normal data. Covariance-based SEM is not robust to high levels of multivariate kurtosis or non-normality [West et al., 1995; Curran et al., 1996; Bentler, 2005; Byrne, 2006]. Unfortunately, data collected via survey instruments assessing the same stimuli commonly have high levels of multivariate kurtosis. This sample proved to be no exception. Evaluation using the Chi-square (χ^2) statistic (or variants of the χ^2 statistic) may not be adequate under these conditions [Hu et al., 1992]. Therefore, corrected fit statistics have been found to be more appropriate [Hu et al., 1992]. Satorra and Bentler [1988] developed a scaling correction for the χ^2 statistic which has been shown to be most reliable [Satorra and Bentler, 1988; Hu et al., 1992]. This article evaluates a model's fit based on the Satorra-Bentler scaled (S-B χ^2) fit indices.
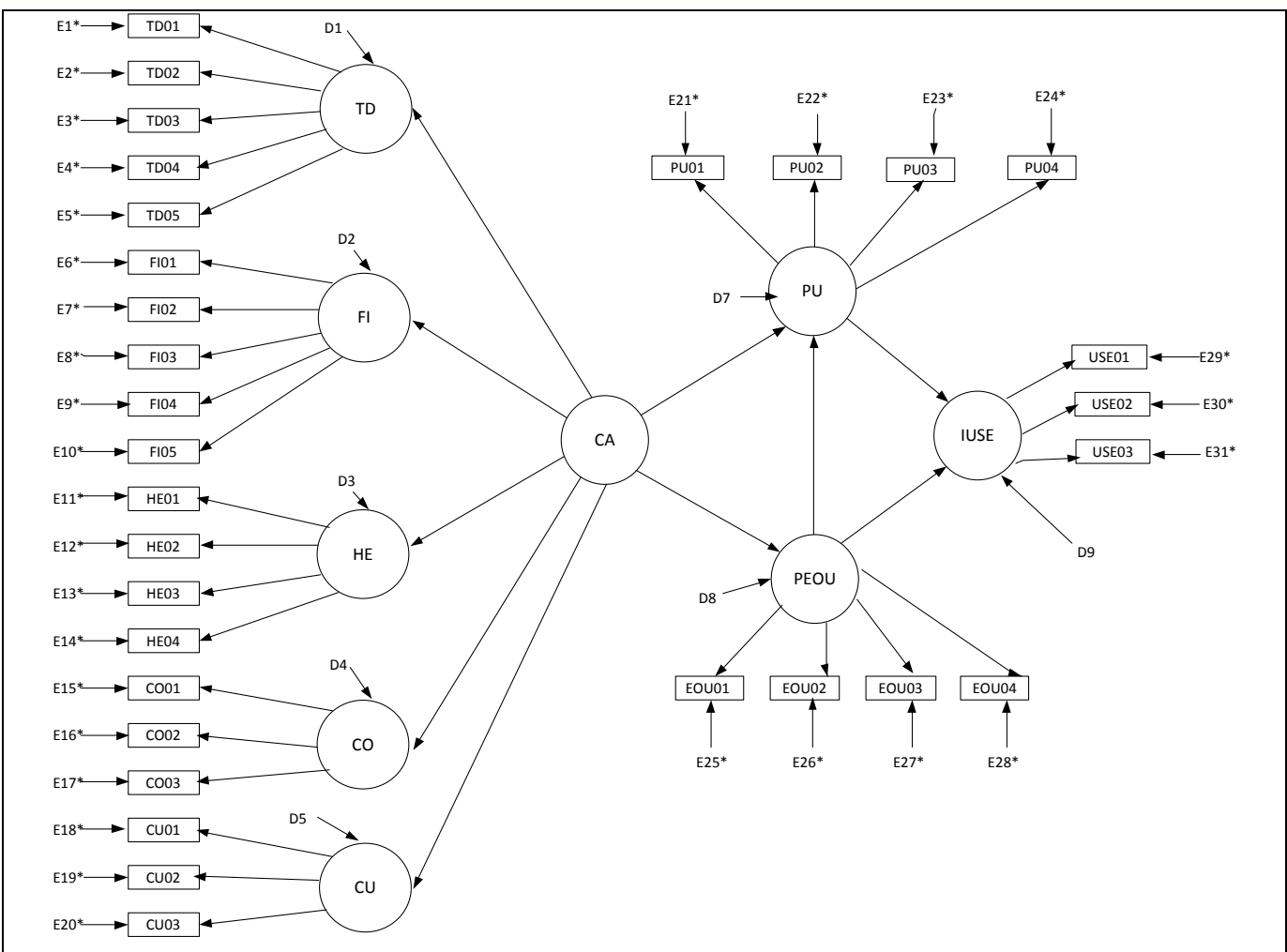
Figure 9. Structural Model

The structural model exhibits good model fit (χ^2 = 866.94, d.f. = 424; CFI = 0.93; RMSEA = 0.057, 90% C.I. = 0.052, 0.063). Robust parameter estimates for the structural paths are also reported here. Our results suggest that cognitive absorption is positively related to perceived usefulness (β = 0.44, p < .001) and perceived ease of use (β = 0.65, p < .001). Perceived ease of use is positively related to perceived usefulness (β = .42, p < .001) and intention to use (β = 0.21, p < .01). Finally, perceived usefulness is positively related to intention to use (β = .49, p < .001). The model explains 61.3 percent of the variance in perceived usefulness, 42.7 percent of the variance in perceived ease of use, and 43.0 percent of the variance in intention to use. Table 7 provides inter-construct correlations and reliability estimates. In the next section, we use component-based SEM to test the same research model.

Table 7: Inter-Construct Correlations and Reliability Estimates											
Construct[*]	Composite Reliabilities	Cronbach's alpha	1	2	3	4	5	6	7	8	9
(1) Temporal Dissociation	0.96	.95									
(2) Focused Immersion	0.87	.81	.44								
(3) Heightened Enjoyment	0.90	.84	.59	.55							
(4) Control	0.82	.65	.51	.47	.63						
(5) Curiosity	0.97	.95	.46	.42	.57	.49					
(6) Cognitive Absorption	0.89	-	.69	.64	.86	.74	.67				
(7) Perceived Usefulness	0.93	.94	.49	.46	.61	.53	.47	.72			
(8) Perceived Ease of Use	0.96	.90	.45	.42	.56	.48	.44	.65	.70		
(9) Intention to Use	0.98	.97	.34	.31	.42	.36	.32	.49	.64	.56	

Appropriateness of Second-Order Model

To assess the appropriateness of our second-order model, we used five criteria to compare first-order and second-order factor models: (1) inter-construct correlations at the first-order level; (2) goodness of fit statistics for the two

models; (3) significance of the second-order factor loadings; (4) target coefficient (T) statistics; (5) significance of the structural relationships that connect measurement models to a criterion variable of interest; and (6) the theoretical support for the conceptualization of the construct. We illustrate the application of these criteria as follows.

1. Construct correlations—We first ensured that the first-order factors for cognitive absorption are significantly correlated and of moderate to high magnitude [Segars, 1997]. We find the correlations within cognitive absorption (r = .42 to .63; see Table 7) are all statistically significant at p < 0.01 and of moderate to high magnitude.

2. Goodness of Fit—Model statistics of the first-order factor model (χ^2 = 418.06, d.f. = 160; CFI = 0.93; RMSEA = 0.071) and the second-order factor model (χ^2 = 434.77, d.f. = 165; CFI = 0.92; RMSEA = 0.072) both meet acceptable thresholds. The second-order factor model should be accepted because it is a more parsimonious model with fewer parameters to be estimated and more degrees of freedom [Grover et al., 2002], and it is conceptually consistent with established theory. It is important to realize that the higher-order factors are simply trying to explain the covariation among the first-order factors in a more parsimonious way (i.e., one that requires fewer degrees of freedom). Consequently, even when the higher-order model is able to effectively explain the factor covariations, the goodness-of-fit of the higher-order model can never be better than the corresponding first-order model. Hence, the basic first-order factor model provides a target or optimum fit for the higher-order model, and we refer to it as the target model. See point 4—target coefficient—for more on how the target coefficient captures the relation between the fit of a first-order structure and the corresponding fit of a nested, more restrictive model (e.g., a higher-order factor structure).

3. Second-order loadings—All second-order factor loadings are highly significant (p < 0.001), further providing justification for the second-order factor model [Tippins and Sohi, 2003].

4. Target coefficient—the target coefficient (T) is the ratio of the chi-square of the first-order model to the chi square of the more restrictive model [Marsh and Hocevar, 1985]. The target coefficient has an upper limit of 1, which would only be possible if the relations among the first-order factors could be completely accounted for in terms of the more restrictive model. Our target coefficient value is 0.96, indicating that the second-order factor accounts for 96 percent of the relations among the first-order factors. This finding provides further support for the second-order factor model [Marsh and Hocevar, 1985].

5. Structural relationships—A first-order factor structural model (where each first-order factor of cognitive absorption is structurally linked to both perceived usefulness and perceived ease of use) explains 59.3 percent of the variance in perceived usefulness and 40.2 percent of the variance in perceived ease of use. The second-order factor model explains 61.3 percent of the variance in perceived usefulness and 42.7 percent of the variance in perceived ease of use (see more structural results below). This comparison, without a significance test, supports that the second-order factor model displays a higher variance explained, which indicates a more robust measurement of the construct compared to the first-order factor model.

6. Theoretical support—when interpreting the statistical comparison of these different models, researchers should remember that in the absence of a significance test or accepted *de facto* standards, conceptual frameworks should be used to inform the comparison. This is especially the case when differences may not support significance.

Aggregate Models in Covariance-Based SEM

We detail two ways to estimate a model including aggregate constructs in covariance-based SEM. For both methods, in contrast to superordinate constructs, researchers should not compare congeneric, tau equivalent, and parallel measurement models. The first method is the MIMIC method, and the second is the common factors method. Constraints for aggregate constructs represent different approaches to combine dimensions to form the construct. Researchers can assign the dimensions equal weights or principal component weights. When incorporating an aggregate construct as a cause in a causal model, one must take into account model identification issues. Specifically, the aggregate construct (modeled as a cause) must have paths leading to at least two endogenous variables [MacCallum and Browne, 1993]. However, research shows that results can vary, depending on the endogenous variables used [Kim et al., 2010]. To overcome that limitation, the common factors method has recently been proposed [Treiblmaier, 2011; Chin et al., 2012]. In this method the index is split into different composites and modeled as a reflective construct. Then those composites are used to form an aggregate construct, and the path weights are then fixed. There are three methods for fixing these path weights: using original weights, using replicated weights, and forcing a maximal correlation (see Treiblaier et al., 2011). This is in line with General Guideline 2: When modeling aggregate constructs, researchers should be aware of the strengths and weaknesses of various methods of analyses.

Data Analysis Using Component-Based SEM

We used SmartPLS 2.0 software to analyze our data. The step-by-step instructions for utilizing SmartPLS can be found in Appendix C. Unlike EQS, this software required calculating two measurement models, as well as a structural model. This is in line with Component-based SEM Guideline 1: Researchers should assess the first-order measurement model separately from the second-order structural model.

First, consistent with Agarwal and Karahanna [2000] we estimated a confirmatory factor analysis to confirm the dimensionality of the first-order constructs. Then, using the factor scores of CA's dimensions, we simultaneously estimated the measurement and structural model. Hence, our first step involved constructing a first-order measurement model (see Figure 10).
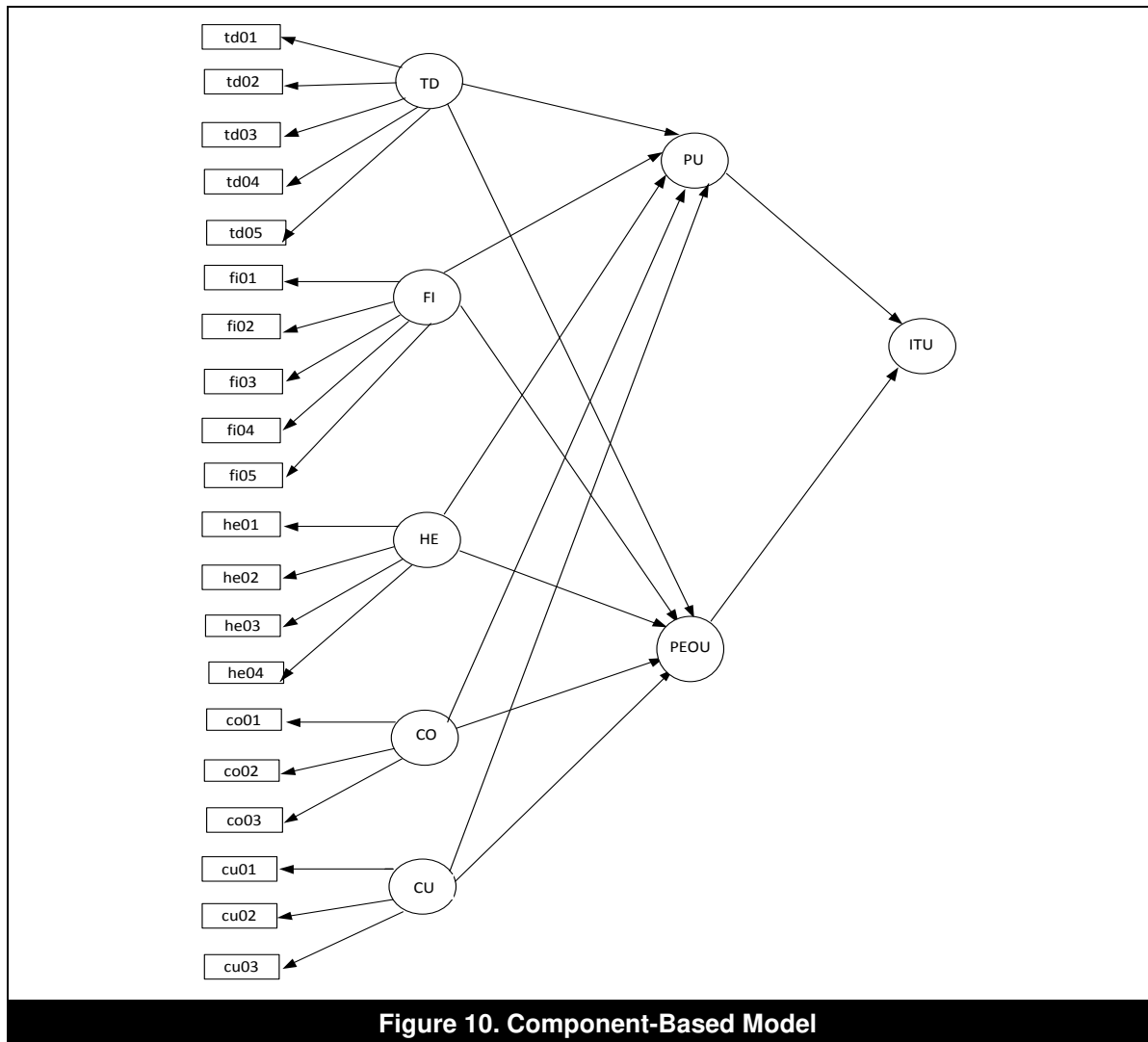
Figure 10. Component-Based Model

We evaluated the reliability, discriminant, and convergent validity of the first-order measurement model for cognitive absorption. Each dimension was modeled as reflective. Using the item loadings, we calculated the internal composite reliability (ICR) to evaluate the measure's reliability. All multi-item dimensions exceeded the .70 threshold for the ICR (see Table 8). Also, to estimate convergent validity, we evaluated each dimension's average variance extracted (AVE). Because each dimension's AVE exceeded .50, our analysis suggests that our measures satisfy heuristics required to support convergent validity [Barclay et al., 1995].

Further, to evaluate discriminant validity we examined the correlations between the dimensions as well as the items. Because the square root of each AVE exceeded the correlation between each dimension and all other dimensions, we were comfortable with the discriminant validity of the measures (see Table 9).

Table 8: First-Order Reliability and AVEs			
Construct	ICR	AVE	Cronbach's α
Intent to Use	0.98	0.94	0.97
Perceived Usefulness	0.96	0.84	0.94
Perceived Ease of Use	0.93	0.76	0.90
CA: Temporal Dissociation	0.96	0.83	0.83
CA: Focused Immersion	0.87	0.60	0.60
CA: Heightened Enjoyment	0.90	0.71	0.71
CA: Control	0.82	0.62	0.62
CA: Curiosity	0.97	0.90	0.90

Table 9: First-Order Correlations of Constructs[a]								
Construct label	IU	PU	PEU	TD	FI	HE	CTL	CRT
Intent to Use (IU)	**.97**							
Perceived Usefulness (PU)	.61	**.92**						
Perceived Ease of Use (PEU)	.53	.66	**.87**					
CA: Temporal Dissociation (TD)	.50	.51	.41	**.91**				
CA: Focused Immersion (FI)	.27	.40	.40	.38	**.77**			
CA: Heightened Enjoyment (HE)	.49	.55	.48	.60	.46	**.84**		
CA: Control (CTL)	.51	.56	.60	.41	.36	.54	**.78**	
CA: Curiosity (CRT)	.25	.42	.33	.31	.41	.60	.42	**.95**
[a] The diagonal element is the square root of the average variance extracted. To be discriminant, the diagonal elements should be larger than all corresponding off-diagonal elements to show discriminant validity.								

As a final step, we compared the item loadings and cross-loadings. We found that all items loaded highest on the construct of interest (see Table 10). Hence, for the first-order measurement model, our analysis provides evidence that the measures are reliable as well as demonstrates adequate convergent and discriminant validity.

Having established discriminant validity in our measurement model, we turned to evaluating the structural model. We used the standardized latent variable scores for each of cognitive absorption's dimensions as indicators of the second-order construct. We then constructed a new model using the latent variable scores as indicators of the multidimensional construct (see Figure 11).
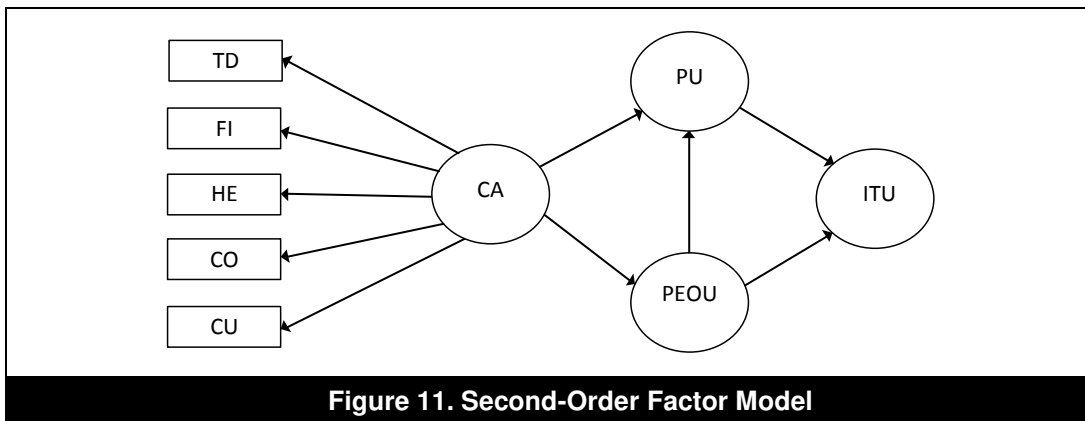
Figure 11. Second-Order Factor Model

We executed the PLS algorithm again (see Figure 11 above) to generate results for our second-order factor model (see Figure 12).

Our results show that cognitive absorption is significantly related to perceived usefulness ($\beta = 0.41$, $p < .001$) and perceived ease of use ($\beta = 0.61$, $p < .001$). Perceived ease of use is positively related to perceived usefulness ($\beta = 0.41$, $p < .001$). Finally, both perceived usefulness ($\beta = 0.46$, $p < .001$) and perceived ease of use ($\beta = 0.22$, $p < .01$) are positively related to intent to use. R^2 values for the endogenous variables are as follows: perceived usefulness ($R^2 = 0.54$), perceived ease of use ($R^2 = 0.37$), and intent to use ($R^2 = 0.40$).

	ITU	PU	PEOU	CA: TD	CA: FI	CA: HE	CA: CO	CA: CU
Table 10: Item Loadings and Cross-Loadings [a]								
ITU1	**0.97**	0.59	0.52	0.50	0.27	0.48	0.50	0.24
ITU2	**0.97**	0.60	0.52	0.47	0.26	0.48	0.49	0.24
ITU3	**0.98**	0.59	0.50	0.49	0.26	0.47	0.50	0.25
PU1	0.60	**0.92**	0.66	0.52	0.37	0.57	0.53	0.41
PU2	0.58	**0.93**	0.57	0.48	0.35	0.53	0.52	0.38
PU3	0.52	**0.93**	0.58	0.45	0.41	0.46	0.51	0.39
PU4	0.52	**0.90**	0.60	0.41	0.36	0.47	0.49	0.36
PEOU1	0.51	0.61	**0.88**	0.39	0.31	0.43	0.59	0.31
PEOU2	0.33	0.41	**0.78**	0.20	0.34	0.26	0.41	0.17
PEOU3	0.51	0.63	**0.92**	0.41	0.36	0.49	0.55	0.31
PEOU4	0.45	0.61	**0.91**	0.39	0.38	0.45	0.52	0.33
CATD1	0.51	0.50	0.40	**0.92**	0.36	0.60	0.44	0.33
CATD2	0.50	0.49	0.37	**0.93**	0.36	0.58	0.39	0.29
CATD3	0.41	0.46	0.40	**0.91**	0.38	0.55	0.42	0.32
CATD4	0.46	0.44	0.36	**0.90**	0.31	0.51	0.32	0.24
CATD5	0.39	0.42	0.34	**0.90**	0.32	0.51	0.31	0.21
CAFI1	0.22	0.32	0.33	0.28	**0.85**	0.34	0.34	0.29
CAFI2	0.32	0.43	0.38	0.46	**0.92**	0.49	0.37	0.41
CAFI3	0.27	0.39	0.37	0.41	**0.92**	0.45	0.33	0.42
CAFI4	0.09	0.10	0.10	0.00	**0.34**	0.11	0.13	-0.02
CAFI5	0.04	0.20	0.24	0.07	**0.68**	0.23	0.14	0.30
CAHE1	0.45	0.49	0.43	0.60	0.44	**0.89**	0.50	0.57
CAHE2	0.43	0.52	0.42	0.57	0.49	**0.93**	0.49	0.60
CAHE3	0.42	0.45	0.42	0.51	0.41	**0.90**	0.46	0.55
CAHE4	0.34	0.39	0.33	0.32	0.15	**0.62**	0.36	0.25
CACO1	0.46	0.52	0.59	0.40	0.39	0.52	**0.91**	0.44
CACO2	0.33	0.32	0.33	0.15	0.06	0.31	**0.54**	0.05
CACO3	0.41	0.45	0.46	0.38	0.34	0.43	**0.85**	0.42
CACU1	0.26	0.39	0.35	0.32	0.41	0.59	0.45	**0.95**
CACU2	0.22	0.38	0.27	0.29	0.39	0.55	0.40	**0.95**
CACU3	0.24	0.41	0.31	0.27	0.36	0.56	0.35	**0.94**

[a] ITU= Intention to Use; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; CA:TD = Cognitive Absorption: Temporal Dissociation; CA:FI = Cognitive Absorption: Focused Immersion; CA: HE = Cognitive Absorption: Heightened Enjoyment; CA:CO = Cognitive Absorption: Control; CA:CU = Cognitive Absorption: Curiosity
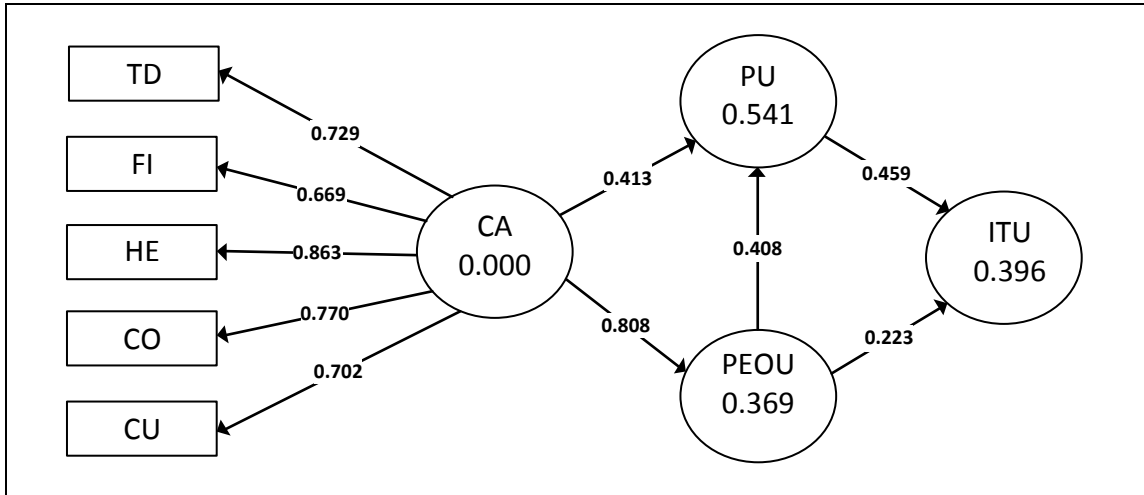
Figure 12. Results for Second-Order Factor Model

Figure 13. Results of Bootstrapped Model
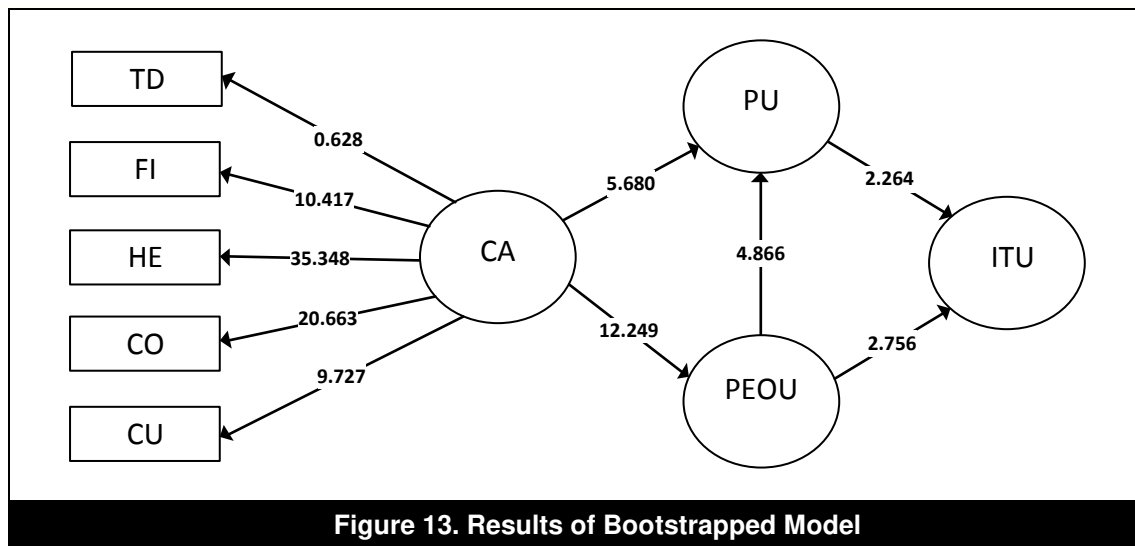
Aggregate Models in Component-Based SEM

To estimate a model including aggregate constructs in component-based SEM, researchers should model the relationship arrows as going from the first-order dimensions to the second-order construct (i.e., in a manner similar to modeling formative constructs). When reporting such analyses, one should be sure to include the dimension weights and their significance. By doing so, readers will be able to understand the relative association of each dimension to the multidimensional construct.

Comparing Covariance-Based SEM and Component-Based SEM

Table 11 details a comparison of how to report and interpret results generated from covariance-based and component-based SEM that incorporate multidimensional constructs. It must be noted that much has been written concerning the use of formative measures in covariance-based SEM. Gefen et al. [2011] summarize the issue by stating this method "presents challenges" [Gefen et al., 2011, p. vi], and several argue that formative measures are problematic when using covariance-based SEM [Edwards, 2011; Treiblmaier, 2011]. On the other hand, formative scales are easily assessed using PLS. Due to the recent literature that provides strong evidence formative indicators may cause stability problems for the construct [Kim et al., 2010; Edwards, 2011], we caution the use of formative indicators without reviewing the issues and concerns. If deemed necessary, a tutorial which outlines how to vet formative indicators has been published [Roberts and Thatcher, 2009].

VI. CONCLUSION

This article was motivated by a desire to "prime the pump" such that IS researchers had access to information on how to conceptually develop and evaluate structural equation models that integrate multidimensional constructs. While such extensive information is available on how to think about all types of multidimensional constructs [Polites et al., 2012], such information is less readily available about how to operationalize these constructs in structural equation models. Additionally, while researchers have provided guidance on how to evaluate the psychometric properties of first-order constructs, a robust understanding of what is necessary for evaluating multidimensional constructs is just beginning to emerge in the IS and research methods literature (see Lewis et al., 2005; Gefen et al., 2011; MacKenzie et al., 2011). In this tutorial, we have taken a step toward providing prerequisite knowledge for using multidimensional constructs in IS research: the practical "how to" in applying these concepts using the specific tools available in today's standard practices. We would like to stress that in doing this we use a specific example which cannot detail every possible type of analyses or construct (e.g., we did not give specific examples of multidimensional constructs beyond the superordinate or aggregate, nor did we illustrate a method other than structural equation modeling). Researchers would be mistaken to apply our guidelines to all forms of multidimensional constructs. Therefore, we suggest that there is a need for additional work that offers guidelines for how to operationalize multidimensional constructs in additional methods as well as different forms of such constructs.

When developing multidimensional constructs, authors should be guided by how theory suggests the form and interrelationship among their dimensions [Law et al., 1998; Edwards, 2001]. This article extends this thought to advance IS research by providing an overview of major types of multidimensional constructs (e.g., superordinate, aggregate, and others). A standard set of terms is outlined that can be used in the IS literature when describing

Table 11. Comparison of Covariance-Based and Component-Based SEM			
	Covariance-based SEM	Component-based SEM	Related Citations[1]
Measurement Model Results (For a complete guide to instrument vetting see MacKenzie et al., 2011.)			
Reliability	Assess using Cronbach's Alpha or Internal Composite Reliability	Assess using Cronbach's Alpha or Internal Composite Reliability	Component—see Gefen and Straub, 2005, p. 93–94.

Covariance—see Brown, 2006, p. 113–126. |
| Dimensionality of the first-order measurement model | A significant improvement in chi-square fit between Model 2 (freely-correlated first-order factors model) and Model 1 (all indicators load on one factor) provides evidence of multidimensionality. | Assess by comparing the item loadings and cross-loadings on each dimension. Not unlike a standard factor analysis, the dimensions' indicators should be discriminant and convergent (cf. Gefen and Straub, 2005). | |
| Convergent Validity | Supported by significant standardized factor loadings of indicators | Supported by the average variance extracted (AVE) of each dimension exceeding 0.50 | |
| Discriminant Validity | Supported by comparing a freely estimated correlation against a constrained correlation between all pairs of first-order factors | Supported by the square root of the AVE of each factor exceeding cross-construct correlations

Supported by indicators loading highest on the dimension of interest | |
| Second-order Construct | Model fit should be compared among parallel, tau equivalent, and congeneric models. Acceptable model fit are suggested by CFI > .9 and RMSEA < .08 [Kline, 2005]. Second-order construct is supported by significant standardized factor loadings of first-order dimensions. | Each dimension's weight and loading on the second-order construct should be reported. Even if weights and loadings are not significant, they should be retained in order to appropriately operationalize the theoretical meaning of the construct. | Component—see Wetzels et al., 2009, p. 184–185.

Covariance—see Brown, 2006, p. 322–325. |
Structural Model Results			
CA with PE	Cognitive absorption is significantly related to perceived usefulness (β = 0.44, p < .001).	Cognitive absorption is significantly related to perceived usefulness (β = 0.41, p < .001).	
CA with PEOU	Cognitive absorption is significantly related to perceived ease of use (β = 0.65, p < .001).	Cognitive absorption is significantly related to perceived ease of use (β = 0.61, p < .001).	

[1] The related citation column is introduced for two purposes. First, it give the reader an understanding of the literature behind each of the measures. Second, it provides a reference so that important statistics (e.g., cut-off values, assumptions) can be easily found.

multidimensional constructs within a nomological network, which should help resolve conceptual inconsistencies in the literature. Further, drawing upon these terms, we illustrate how to use standard procedures to model these complex nomological relationships using contemporary SEM tools. This is important, because, contrary to a popular belief that PLS is the best-suited tool for evaluating multidimensional models [Wetzels et al., 2009], we illustrate that covariance-based and component-based SEM may be used to examine superordinate and aggregate multidimensional constructs. While this belief may have been true in earlier versions of covariance-based SEM, this tutorial illustrates how to estimate such models using EQS, a contemporary covariance-based SEM software application.

While our tutorial demonstrates that covariance-based SEM may be more cumbersome than component-based SEM (e.g., it requires more steps to estimate such multidimensional models), it also permits estimating first- and second-order measurement models in a single structural model. This contrasts with component-based SEM, which requires one to estimate separate models in order to evaluate multidimensional constructs. We do not recommend that authors consider this difference when selecting a technique to estimate a model. Issues such as the state of development of theory, distribution of the data, and sample size should also drive the choice between SEM techniques, not whether the model incorporates a multidimensional construct [Gefen et al., 2000]. By illustrating how to incorporate multidimensional constructs in covariance-based or component-based analysis, this article will

Communications of the Association for Information Systems

hopefully result in authors being able to select the tool best suited for the objectives of their research (e.g., theory testing vs. theory development; see Chin, 1998). By doing so, we believe that researchers will be able to develop richer explanations for technology's implications for individuals and organizations.

REFERENCES

Agarwal, R., and E. Karahanna (2000) "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs About Information Technology Usage," *MIS Quarterly* (24)4, pp. 665–695.

Allison, P.D. (2003) "Missing Data Techniques for Structural Equation Modeling," *Journal of Abnormal Psychology* (112)4, pp. 545–557.

Anderson, J.C., and D.W. Gerbing (1988) "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach," *Psychological Bulletin* (103)3, pp. 411–423.

Bagozzi, R.P. (1985) "Expectancy-Value Attitude Models: An Analysis of Critical Theoretical Issues," *International Journal of Research Marketing* (2), pp. 43–60.

Bagozzi, R.P. (1988) "The Rebirth of Attitude Research in Marketing," *Journal of the Market Research Society* (30)2, pp. 163–195.

Bagozzi, R.P., and J.R. Edwards (1998) "A General Approach for Representing Constructs in Organizational Research," *Organizational Research Methods* (1)1, pp. 45–87.

Barclay, D., C. Higgins, and R. Thomson (1995) "The Partial Least Squares Approach (PLS) to Causal Modeling, Personal Computer Adoption and Use as an Illustration," *Technology Studies* (2)2, pp. 285–309.

Becker, T.E., and R.S. Billings (1993) "Profiles of Commitment: An Empirical Test," *Journal of Organizational Behavior* (14)2, pp. 177–190.

Bentler, P.M. (1990) "Comparative Fit Indexes in Structural Models," *Psychological Bulletin* (107)2, pp. 238–246.

Bentler, P.M. (2005) *EQS 6 Structural Equations Program Manual*, Encino, CA: Multivariate Software.

Bollen, K., and R. Lennox (1991) "Conventional Wisdom on Measurement: A Structural Equation Perspective," *Psychological Bulletin* (110)2, pp. 305–314.

Bollen, K.L. (1989) *Structural Equations with Latent Variables*, New York, NY: John Wiley.

Boomsma, A. (2000) "Reporting Analyses of Covariance Structures," *Structural Equation Modeling* (7)3, pp. 461–483.

Brown, T.A. (2006) *Confirmatory Factory Analysis for Applied Research,* New York, NY: The Guilford Press.

Byrne, B.M. (2006) *Structural Equation Modeling with EQS: Basic Concepts, Applications, and Programming,* Mahwah, NJ: Lawrence Erlbaum Associates.

Campbell, D.T., and D.W. Fiske (1959) "Convergent and Discriminant Validation by the Multitrait-multimethod Matrix," *Psychological Bulletin* (56), pp. 81–105.

Chan, Y.E., S.L. Huff, D.W. Barclay, and D.G. Copeland (1997) "Business Strategic Orientation, Information Systems Strategic Orientation, and Strategic Alignment," *Information Systems Research* (8)2, pp. 125–150.

Chin, W., J.B. Thatcher, and R.T. Wright (2012) "Assessing Common Method Variance: Assessing the UMLC Approach," *MIS Quarterly,* forthcoming.

Chin, W.W. (1998) "Issues and Opinion on Structural Equation Modeling," *Management Information Systems Quarterly* (22)1, pp. vii-xvi.

Chin, W.W. (2010) "How to Write Up and Report PLS Analyses," in Vinzi, V.E., W.W. Chin, and J. Henseler, *Handbook of Partial Least Squares: Concepts, Methods and Applications,"* New York, NY: Springer.

Chin, W.W., and A. Gopal (1995) "Adoption Intention in GSS: Relative Importance of Beliefs," *Data Base* (26)2/3, pp. 42–64.

Chwelos, P., I. Benbasat, and A.S. Dexter (2001) "Research Report: Empirical Test of an EDI Adoption Model," *Information Systems Research* (12)3, pp. 304–321.

Compeau, D.R., and C.A. Higgins (1995) "Computer Self-efficacy: Development of a Measure and Initial Test," *MIS Quarterly* (19)2, pp. 189–211.

Curran, P.J., S.G. West, and J.F. Finch (1996) "The Robustness of Test Statistics to Non-normality and Specification Error in Confirmatory Factor Analysis," *Psychological Methods* (1), pp. 16–29.

Davis, F.D. (1989) "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13)3, pp. 319–340.

Davis, F.D., R.P. Bagozzi, and P.R. Warshaw (1989) "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science* (35)8, pp. 982–1003.

Diamantopoulos, A., and H. Winklhofer (2001) "Index Construction with Formative Indicators: An Alternative to Scale Development," *Journal of Marketing Research* (38)2, pp. 269–277.

Duncan, R.B. (1972) "Characteristics of Organizational Environments and Perceived Environmental Uncertainty," *Administrative Science Quarterly* (17)3, pp. 313–327.

Edwards, J.R. (2001) "Multidimensional Constructs in Organizational Behavior Research: An Integrative Analytical Framework," *Organizational Research Methods* (4)2, pp. 144–192.

Edwards, J.R. (2009) "Latent Variable Modeling in Congruence Research: Current Problems and Future Directions," *Organizational Research Methods* (12)1, pp. 34–62.

Edwards, J.R. (2011) "The Fallacy of Formative Measurement," *Organization Research Methods* (14)2, pp. 370–388.

Edwards, J.R., and R.P. Bagozzi (2000) "On the Nature and Direction of the Relationship Between Constructs and Measures," *Psychological Methods* (5)2, pp. 155–174.

Gefen, D., E.E. Rigdon, and D. Straub (2011) "An Update and Extension to SEM Guidelines for Administrative and Social Science Research," *MIS Quarterly* (35)2, pp. iii–xiv.

Gefen, D., and D. Straub (2005) "A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example," *Communications of the Association for Information Systems* (16) Article 5, pp. 91–109.

Gefen, D., D.W. Straub, and M.-C. Boudreau (2000) "Structural Equation Modeling and Regression: Guidelines for Research Practice," *Communications of the Association Information Systems* (4)7, pp. 1–77.

Gold, A.H., A. Malhotra, and A.H. Segars (2001) "Knowledge Management: An Organizational Capabilities Perspective," *Journal of Management Information Systems* (18)1, pp. 185–214.

Graham, J.M. (2006) "Congeneric and (Essentially) Tau-Equivalent Estimates of Score Reliability: What They Are and How to Use Them," *Educational and Psychological Measurement* (66)6, pp. 930–944.

Grover, V., J.T.C. Teng, and K.D. Fiedler (2002) "Investigating the Role of Information Technology in Building Buyer–Supplier Relationships," *Journal of the Association for Information Systems* (3)7, pp. 217–245.

Hair, J.F., R.E. Anderson, R.L. Tathem, and W.C. Black (1998) *Multivariate Data Analysis,* Upper Saddle River, NJ: Prentice Hall.

Hanisch, K.A., and C.L. Hulin (1991) "General Attitudes and Organizational Withdrawal: An Evaluation of a Causal Model," *Journal of Vocational Behavior* (39)1, pp. 110–128.

Hardin, A.M., J.C.-J. Chang, and M.A. Fuller (2008) "Formative vs. Reflective Measurement: Comment on Marakas, Johnson, and Clay (2007)," *Journal of the Association for Information Systems* (9)9, pp. 519-534.

Harman, H.H. (1976) *Modern Factor Analysis,* Chicago, IL: University of Chicago Press.

Howell, R.D., E. Breivik, and J.B. Wilcox (2007) "Reconsidering Formative Measurement," *Psychological Methods* (12)2, pp. 205–218.

Hu, L.T., P.M. Bentler, and Y. Kano (1992) "Can Test Statistics in Covariance Structure Analysis Be Trusted?" *Psychological Bulletin* (112)2, pp. 351–362.

Hunter, J.E., and D.W. Gerbing (1982) "Unidimensional Measurement, Second Order Factor Analysis, and Causal Models," in Staw, B.M., and L.L. Cummings, *Research in Organizational Behavior,* Greenwich, CT: JAI Press, pp. 267–320.

Jarvis, C.B., S.B. Mackenzie, and P.M. Podsakoff (2003) "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research," *Journal of Consumer Research* (30)2, pp. 199–218.

Joreskog, K.G., and A.S. Goldberger (1975) "Estimation of a Model with Multiple Indicators and Multiple Causes of a Single Latent Variable," *Journal of the American Statistical Association* (70)351, pp. 631–639.

Karahanna, E., R. Agarwal, and C.M. Angst (2006) "Reconceptualizing Compatibility Beliefs in Technology Acceptance Research," *MIS Quarterly* (30)4, pp. 781–804.

Kim, G., B. Shin, and V. Grover (2010) "Investigating Two Contradictory Views of Formative Measurement in Information Systems Research," *MIS Quarterly* (34)2, pp. 345–366.

Klein, R. (2006) "Internet-Based Patient-Physician Electronic Communication Applications: Patient Acceptance and Trust," *e-Service Journal* (5)2, pp. 27–51.

Kline, R.B. (2005) *Principles and Practice of Structural Equation Modeling,* New York, NY: The Guilford Press.

Law, K.S., C.-S. Wong, and W.H. Mobley (1998) "Toward a Taxonomy of Multidimensional Constructs," *Academy of Management Review* (23)4, pp. 741–755.

Law, K.S., and C.S. Wong (1999) "Multidimensional Constructs in Structural Equation Analysis: An Illustration Using the Job Perception and Job Satisfaction Constructs," *Journal of Management* (25)2, pp. 143–160.

Lewis, B.R., G.F. Templeton, and T.A. Byrd (2005) "A Methodology for Construct Development in MIS Research," *European Journal of Information Systems* (14), pp. 388–400.

Li, X., T.J. Hess, and J.S. Valacich (2008) "Why Do We Trust New Technology? A Study of Initial Trust Formation with Organizational Information Systems," *Journal of Strategic Information Systems* (17), pp. 39–71.

Little, R.J.A., and D.A. Rubin (1987) *Statistical Analysis with Missing Data*, New York, NY: John Wiley & Sons.

Lohmöller, J.-B. (1989) *Latent Variable Path Modeling with Partial Least Squares,* Heidelberg, Germany: Physica-Verlag.

Lu, H.P., H.J. Yu and S.S.K. Lu (2001) "The Effects of Cognitive Style and Model Type on DSS Acceptance: An Empirical Study," *European Journal of Operational Research* (131)3, pp. 649–663.

MacCallum, R.C., and M.W. Browne (1993) "The Use of Causal Indicators in Covariance Structure Models: Some Practical Issues," *Psychological Bulletin* (114)3, pp. 533–541.

MacKenzie, S.B., P.M. Podsakoff, and N.P. Podsakoff (2011) "Construct Measurement and Validation Procedure in MIS and Behavior Research: Integrating New and Exisiting Techniquies," *MIS Quarterly* (35)2, pp. 293–334.

Marakas, G., R. Johnson, and P.F. Clay (2007) "The Evolving Nature of the Computer Self-efficacy Construct: An Empirical Investigation of Measurement Construction, Validity, Reliability and Stability over Time," *Journal of the Association for Information Systems* (8)1, pp. 15-46.

Marakas, G., R.D. Johnson, and P.F. Clay (2008) "Formative vs. Reflective Measurement: A Reply to Hardin, Chang, and Fuller," *Journal of the Association for Information Systems* (9)9, pp. 535-566.

Marakas, G.M., M.Y. Yi, and R.D. Johnson (1998) "The Multilevel and Multifaceted Character of Computer Self-efficacy: Toward Clarification of the Construct and an Integrative Framework for Research," *Information Systems Research* (9)2, pp. 126–163.

Marsh, H.W., and D. Hocevar (1985) "Application of Confirmatory Factor Analysis to the Study of Self Concept: First and Higher Order Factor Models and Their Invariance Across Groups," *Psychological Bulletin* (97)3, pp. 562–582.

McKnight, D.H., V. Choudhury, and C. Kacmar (2002) "Developing and Validating Trust Measures for e-Commerce: An Integrative Typology," *Information Systems Research* (13)3, pp. 334–359.

Ones, D.S., and C. Viswesvaran (1996) "Bandwidth-Fidelity Dilemma in Personality Measurement for Personnel Selection," *Journal of Organizational Behavior* (17)6, pp. 609–626.

Petter, S., D. Straub, and A. Rai (2007) "Specifying Formative Constructs in Information Systems Research," *MIS Quarterly* (31)4, pp. 623–656.

Polites, G., N. Roberts, and J. Thatcher (2012) "Conceptualizing Models Using Multidimensional Constructs: A Conceptual Review and Guidelines for Their Use," *European Journal of Information Systems* (21)1, pp. 22–48.

Qureshi, I., and D. Compeau (2009) "Assessing Between-Group Differences in Information Systems Research: A Comparison of Covariance- and Component-Based SEM," *MIS Quarterly* (33)1, pp. 197–214.

Rai, A., R. Patnayakuni, and N. Seth (2006) "Firm Performance Impacts of Digitally Enabled Supply Chain Integration Capabilities," *MIS Quarterly* (30)2, pp. 225–246.

Rindskopf, D., and T. Rose (1988) "Some Theory and Applications of Confirmatory Second-order Factor Analysis," *Multivariate Behavioral Research* (23), pp. 51–67.

Roberts, N., and J. Thatcher (2009) "Conceptualizing and Testing Formative Constructs: Tutorial and Annotated Example," *Database* (40)3, pp. 9–39.

Satorra, A.C., and P.M. Bentler (1988) *Scaling Corrections for Chi-square Statistics in Covariance Structure Analysis*, Proceedings of the Business and Economics Sections, Alexandria, VA: American Statistical Association.

Segars, A. (1997) "Assessing the Unidimensionality of Measurement: A Paradigm and Illustration Within the Context of Information Systems Research," *Omega* (25)1, pp. 107–121.

Shin, B., and G. Kim (2011) "Investigating the Reliability of Second-Order Formative Measurement in Information Systems Research," *European Journal of Information Systems* (20)5, pp. 608–623.

Straub, D., M.-C. Boudreau, and D. Gefen (2004) "Validation Guidelines for IS Positivist Research," *Communications of the Association for Information Systems* (13) Article 24, pp. 380–427.

Sun, H., and Y. Fang (2010) *Toward a Model of Mindfulness in Technology Acceptance,* International Conference on Information Systems, St. Louis, MO: AIS eLibrary.

Swanson, E.B., and E. Dans (2000) "System Life Expectancy and the Maintenance Effort: Exploring Their Equilibration," *MIS Quarterly* (24)2, pp. 277–297.

Tanriverdi, H. (2006) "Performance Effects of Information Technology Synergies in Multibusiness Firms," *MIS Quarterly* (30)1, pp. 57–77.

Teo, H.H., K.K. Wei, and I. Benbasat (2003) "Predicting Intention to Adopt Interorganizational Linkages: An Institutional Perspective," *MIS Quarterly* (27)1, pp. 19–50.

Tippins, M.J., and R.S. Sohi (2003) "IT Competency and Firm Performance: Is Organizational Learning a Missing Link?" *Stretegic Management Journal* (18)8, pp. 745–761.

Treiblmaier, H., P.M. Bentler, and P. Mair (2011) "Formative Constructs Implemented via Common Factors," *Structural Equation Modeling* (18)1, pp. 1–17.

Venkatraman, N. (1989) "Strategic Orientation of Business Enterprises: The Construct, Dimensionality, and Measurement," *Management Science* (35)8, pp. 942–962.

Wang, D., L. Xuy, and H.C. Chanz (2008) *Understanding Users' Continuance of Facebook: The Role of General and Specific Computer Self-efficacy,* International Conference on Information Systems, Montreal, PQ: AIS eLibrary.

West, S.G., J.F. Finch, and P.J. Curran (1995) "Structural Equation Models with Nonnormal Variables: Problems and Remedies," in Hoyle, R.H., *Structural Equation Modeling: Concepts, Issues, and Applications,* Thousand Oaks, CA: Sage, pp. 56–75.

Wetzels, M., G. Odekerken-Schroder, and C. van Oppen (2009) "Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustrations," *MIS Quarterly* (33)1, pp. 177–195.

Wong, C.S., K.S. Law, and G.-H. Huang (2008) "On the Importance of Conducting Construct-level Analysis for Multidimensional Constructs in Theory Development and Testing," *Journal of Management* (34)4, pp. 744–764.

Zhu, K. (2004) "The Complementarity of Information Technology Infrastructure and E-Commerce Capability: A Resource-Based Assessment of Their Business Value," *Journal of Management Information Systems* (21)1, pp. 167–202.

APPENDIX A: STEP-BY-STEP INSTRUCTIONS USING EQS

To help facilitate this tutorial we have posted the item correlation matrix at www.usf-research.org/CAIS-Wright.

To start, we need to establish convergent and discriminant validity. To do so we will run multiple measurement models in EQS. Initially, we open our model data in EQS (for detailed direction on this, see the EQS manual). After the data is loaded, we click on the "New Model Builder" button in the toolbar. Although we provide detailed step-by-step instructions, readers interested in more details concerning EQS are directed to excellent resources [Byrne, 2006]. Then we click on the "Diagram Window" button.

The toolbar for the diagram helper is shown in Figure A-1. For our purposes, we will use four tools in particular: model direct one-way paths (these can be paths between constructs and indicators, as well as paths between constructs), insert variables (i.e., indicators, manifest variables), insert factors (i.e., constructs, latent variables), and model covariances. For the sake of consistency, we refer to measured or manifest variables as indicators, and constructs or latent variables as factors.
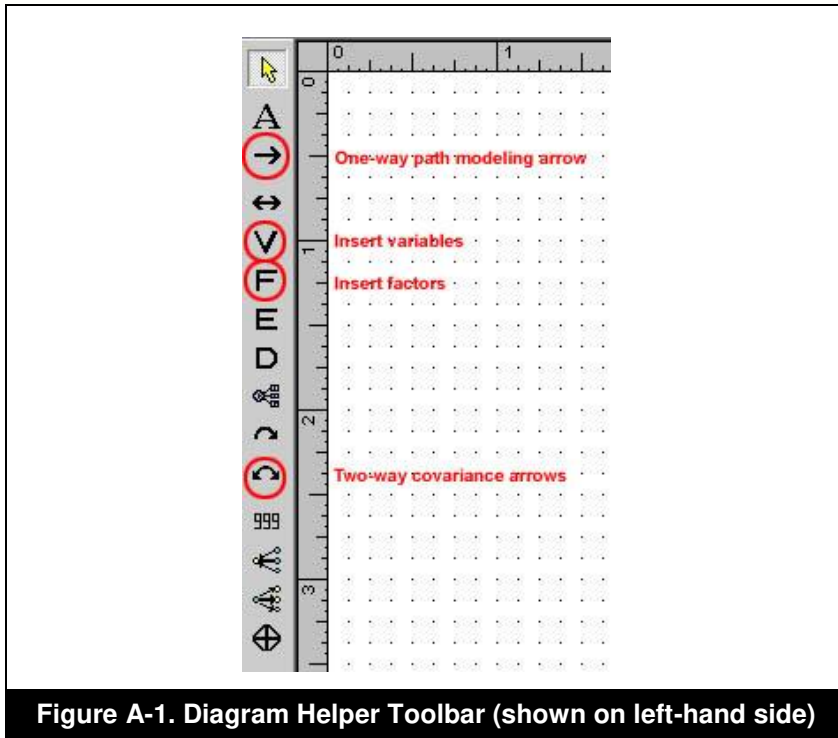
Figure A-1. Diagram Helper Toolbar (shown on left-hand side)

We click the variable button and then click in the blank screen to assign indicators, which displays the indicators in our data set. To do so we click the "V" button (insert variables) on the toolbar. Then we click on any area in the diagram window (i.e., white space) to generate a dialog box in which we can select indicators to include in our model. We select all of the indicators we wish to use (some or all of the indicators can be selected at one time). Then we transfer the indicators we wish to use to the right column, and click "OK" (see Figure A-2).
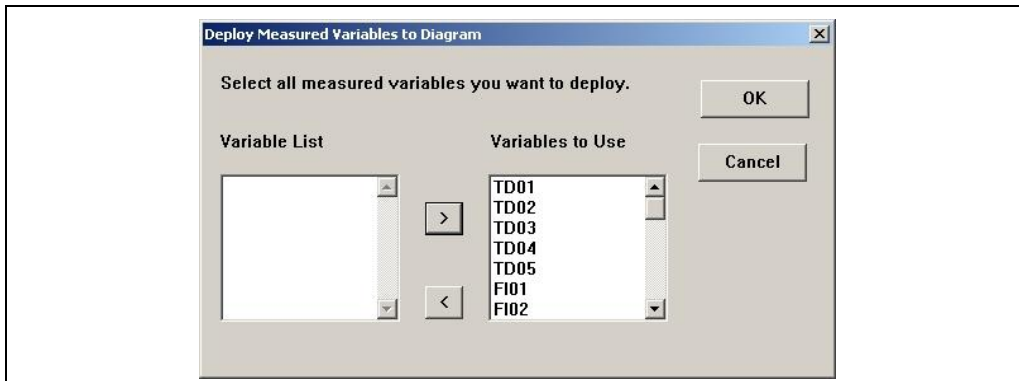
Figure A-2. Transferring Indicators from "Variable List" to "Variables to Use"

The indicators will then appear in the diagram window. We can move the indicators around the diagram by selecting the yellow arrow. We will organize the indicators to prepare for the confirmatory factor analyses. The insertion of indicators is completed in the same way for every model. Alternatively, once the indicators are inserted, the model can simply be rearranged after each analysis.

Model 1: First-Order Factor Model

Our first measurement model tests for the multidimensionality of cognitive absorption. Specifically, we hypothesize that a unidimensional first-order factor model accounts for the variance among all twenty indicators. We model factors (i.e., latent variables) by selecting the factor ("F") button and clicking in the diagram window. Like the indicator insertion process, we must click on the "F" button and then click on an area in the diagram window in order to create new factors.

For ease of reference, we can assign labels to the factors by double clicking on them. In this case, we change the label of F1 to CA (see Figure A-3).
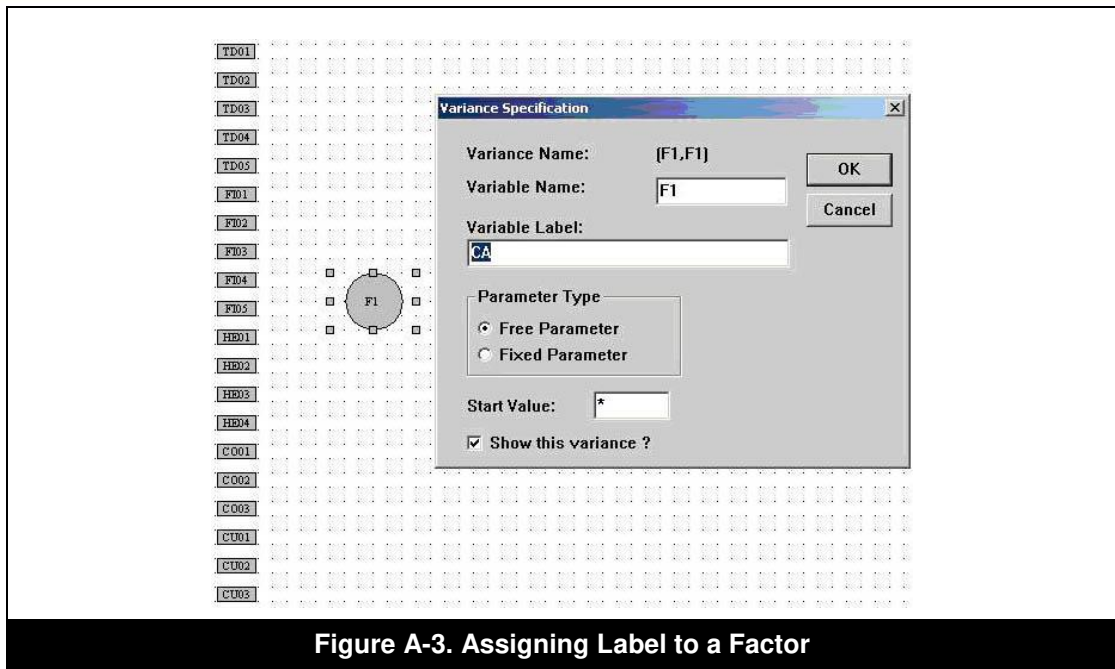
Figure A-3. Assigning Label to a Factor

Next, we assign the indicators to the factor by selecting the one-way path drawing arrow (see Figure A1 above). It is important to note that the direction in which we draw the arrow designates the path as either reflective or formative. In order to assign reflective paths, we first click the factor, and then the indicator. We repeat the process to assign all of the indicators to the factor. Figure A-4 depicts CA as a unidimensional factor.
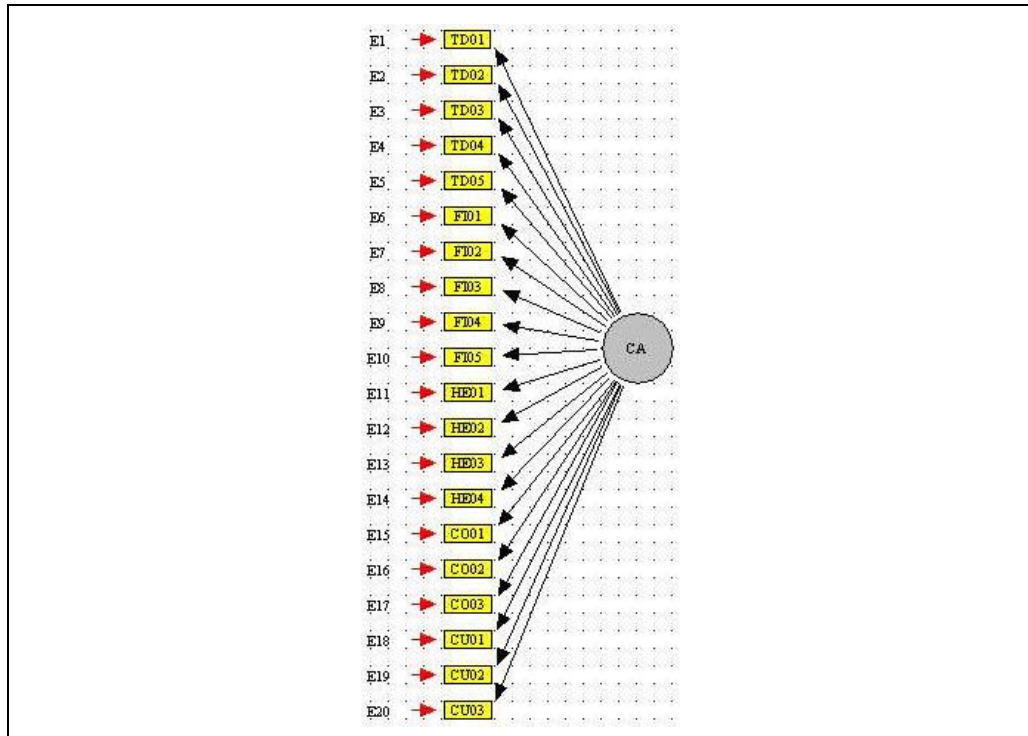
Figure A-4. Modeling Cognitive Absorption as a Unidimensional Factor

In order to assign a measurement scale to each factor, we must fix a single indicator path for each factor to be 1.0 [Kline, 2005]. In order to fix a parameter at 1.0, we double click on a path and select "Fixed Parameter" (see Figure A-5).
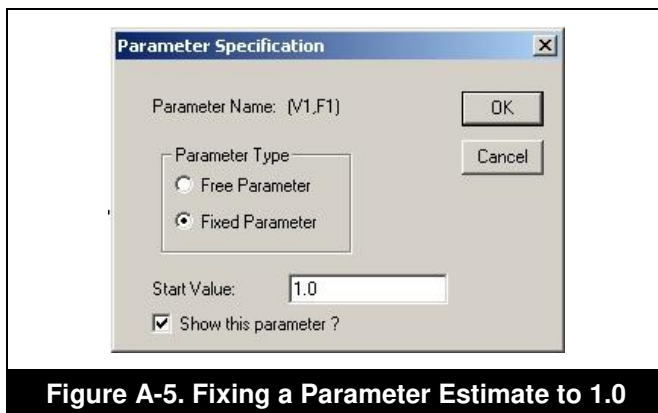
Figure A-5. Fixing a Parameter Estimate to 1.0

To run our model, we must generate the EQS command file. We do this by selecting "Build EQS" and then clicking "Title/Specifications."

We note that a traditional assumption in SEM is that the relationship between the observed variables and their constructs and between one construct and another is linear [Gefen et al., 2000]. Historically, covariance-based SEM software had no tools for handling variations from this assumption. However, EQS 6.1 provides statistics (e.g., model fit, parameter estimates) which are robust to non-normality [Byrne, 2006]. To generate robust method statistics, we select the "robust methods" option in the EQS Model Specifications window (see Figure A-6). This window will appear automatically when we build the EQS command file (as performed in the previous step). It is important to note that EQS must have access to the original data in order to leverage robust methods. EQS cannot leverage robust methods with only a correlation or covariance matrix.
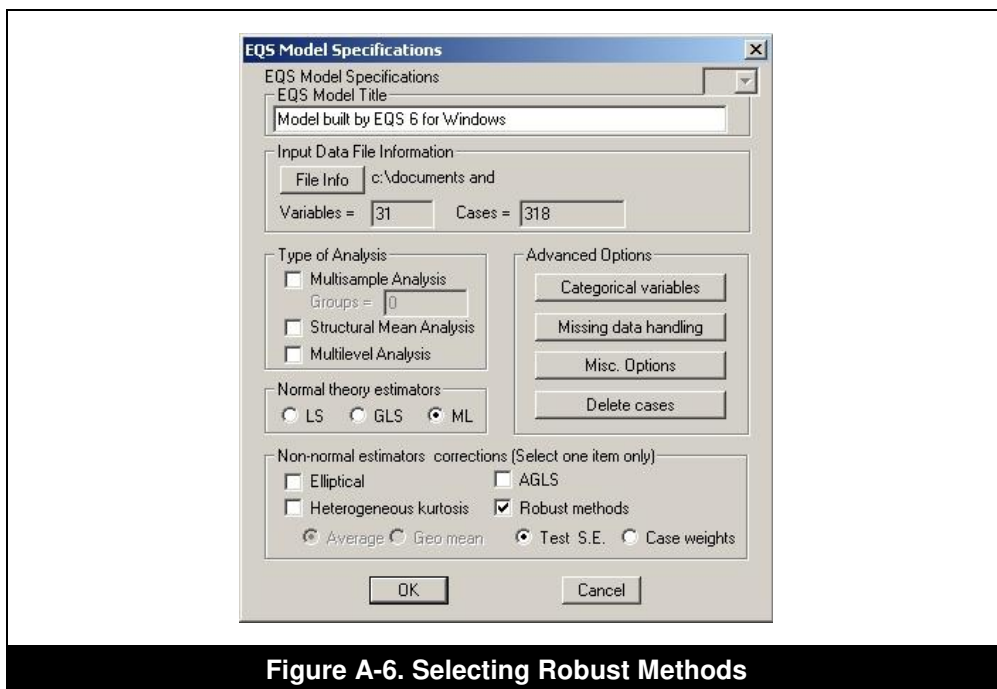
Figure A-6. Selecting Robust Methods

After clicking "OK," EQS generates the command file. From here, we can insert certain options into the command file. To request additional output, we select "Build EQS" and "Print."

Of the available options, we select "Model Correlation Matrix" (this option provides construct-level correlations, see Figure A-7). For more information regarding additional output options, see Byrne [2006].
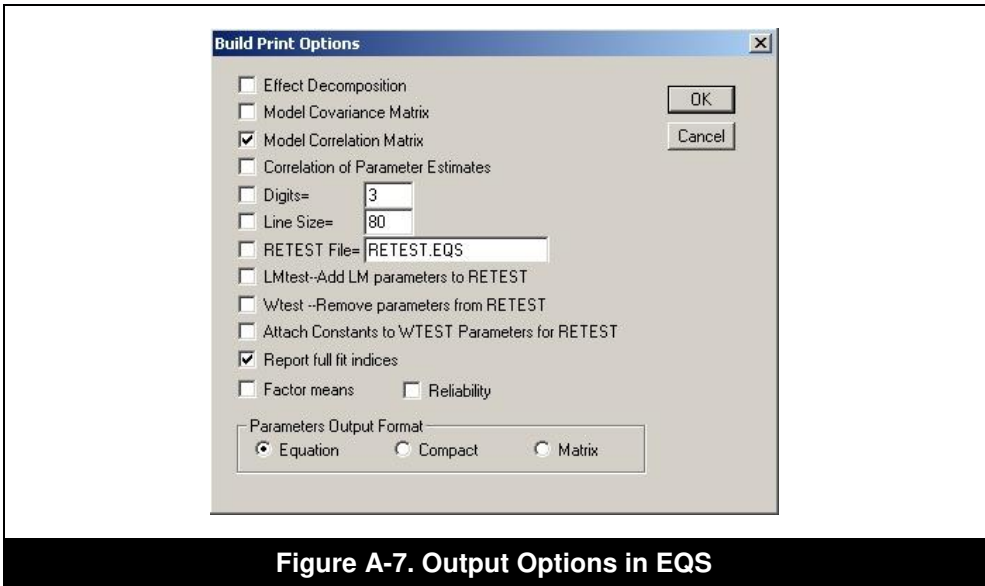
Figure A-7. Output Options in EQS

We will accept these options by clicking "OK." We execute the model by clicking "Build EQS" and selecting "Run EQS."

Model 2: Dimensionality and Convergent Validity

In the second model, we establish different first-order factors for each dimension of cognitive absorption. We aim to provide evidence of multidimensionality and convergent validity. Specifically, in this model we hypothesize that the twenty indicators form into five freely correlated first-order factors.

First we will place latent factors for each construct. Then we assign the indicators to the latent factors by selecting the path drawing arrow. We designate the paths as reflective by drawing the paths from the factors to the indicators. Also, we fix the path for one indicator at 1.0 for each factor. Figure A-8 depicts Model 2 (without covariances).
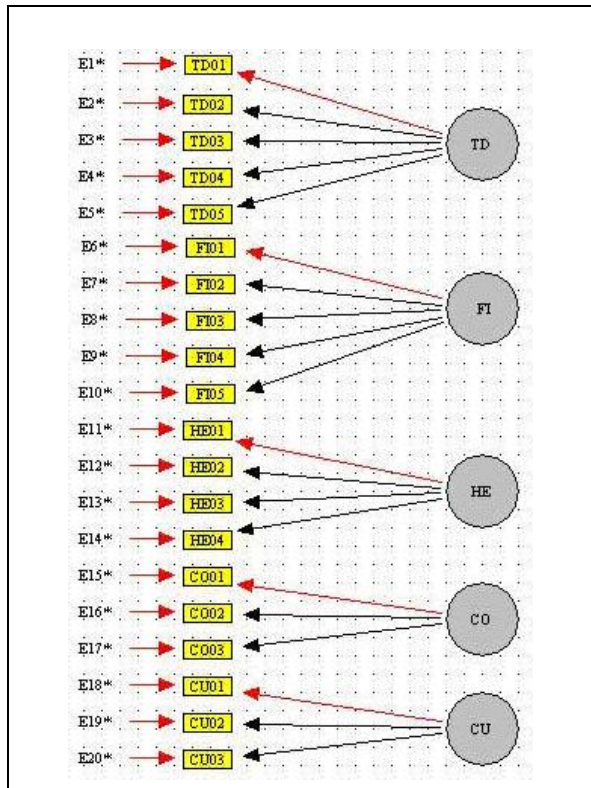
Figure A-8. Model 2 Without Covariances

We allow each factor to freely covary with other factors. We use the two-way covariance button to assign a covariance between each pair of factors. After assigning all of the covariances, our model appears as follows in Figure A-9.
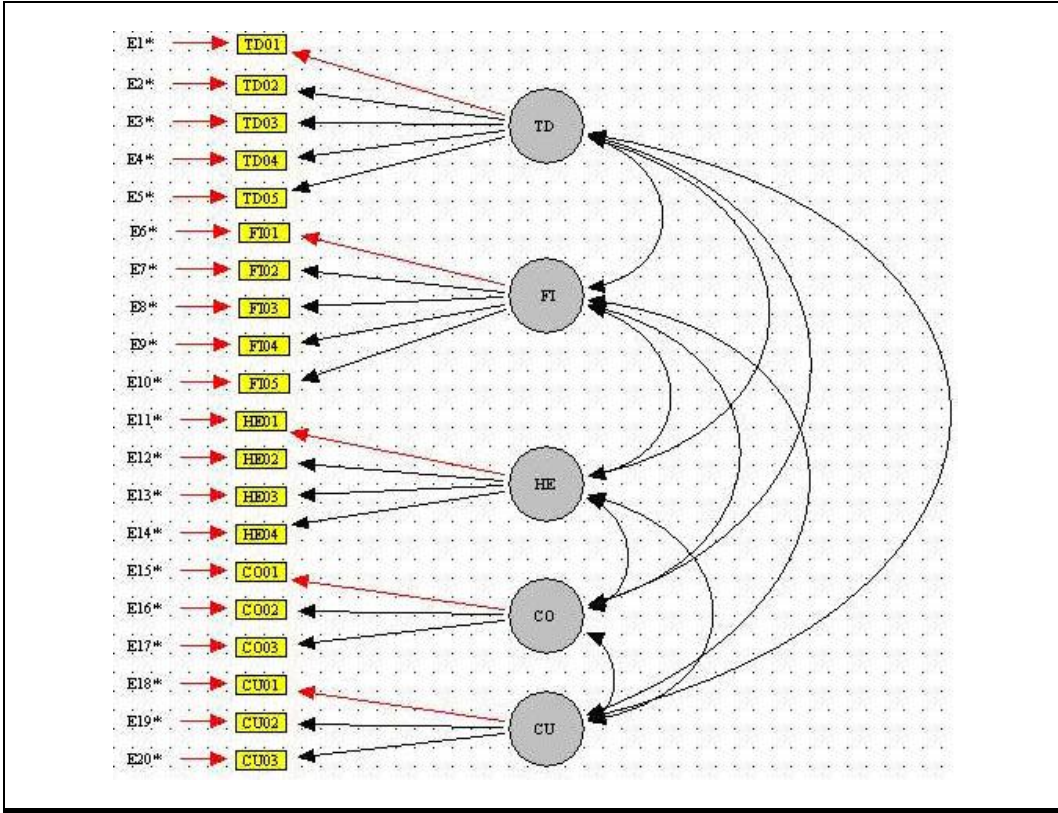
Figure A-9. Model 2

Next, we generate the EQS command file. We select the "Robust methods" option in the EQS model specifications window. We then run our model. The resulting standardized parameter estimates are presented in Figure A-10.
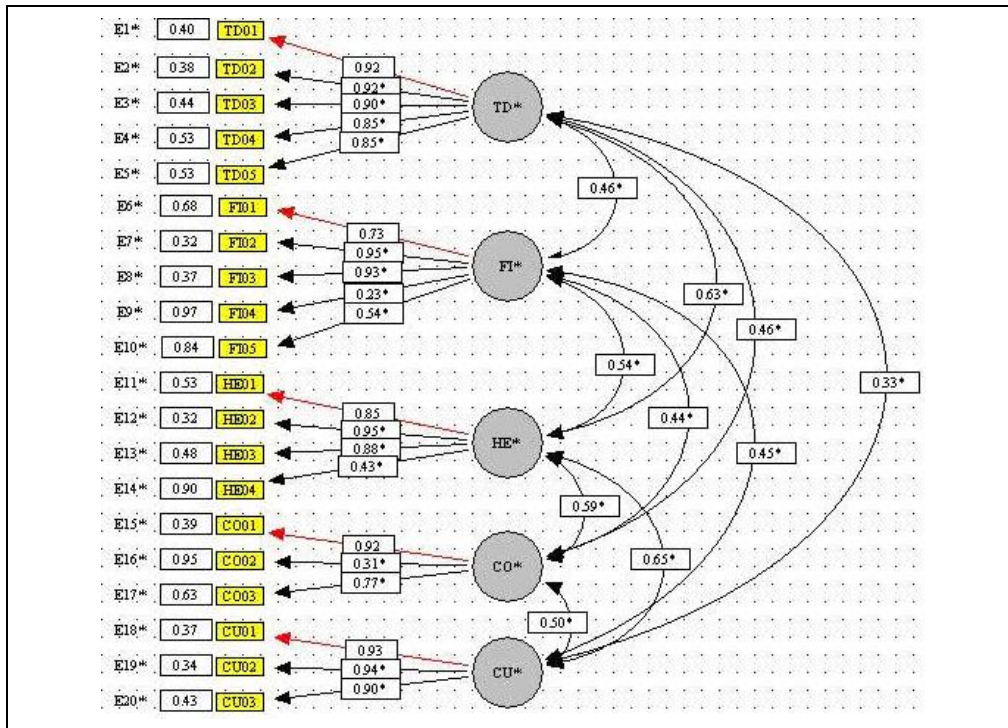
Figure A-10. Standardized Solution for Model 2

Model 3: Discriminant Validity

In the third model, we will establish that each first-order factor is discriminant from the other first-order factors. We do this by creating a model with just two first-order factors. First, we run a confirmatory factor analysis (CFA) with a pair of factors allowed to freely covary. Then we constrain the covariance to 1.0. We then evaluate the change in χ2 across the models. If constraining the covariance to 1.0 significantly hampers the χ2 statistic, then we have evidence of discriminant validity [Venkatraman, 1989]. In other words, the two first-order factors represent two distinctly different factors and do not perfectly covary. However, if constraining the covariance does not significantly hamper model fit, then the two first-order factors may not be significantly different.

First, we designate two first-order-factors: Temporal Dissociation and Focused Immersion (see Figure A-11). We demonstrate how to run the analysis for the first pair of factors. The process must be repeated for each unique pair of factors.
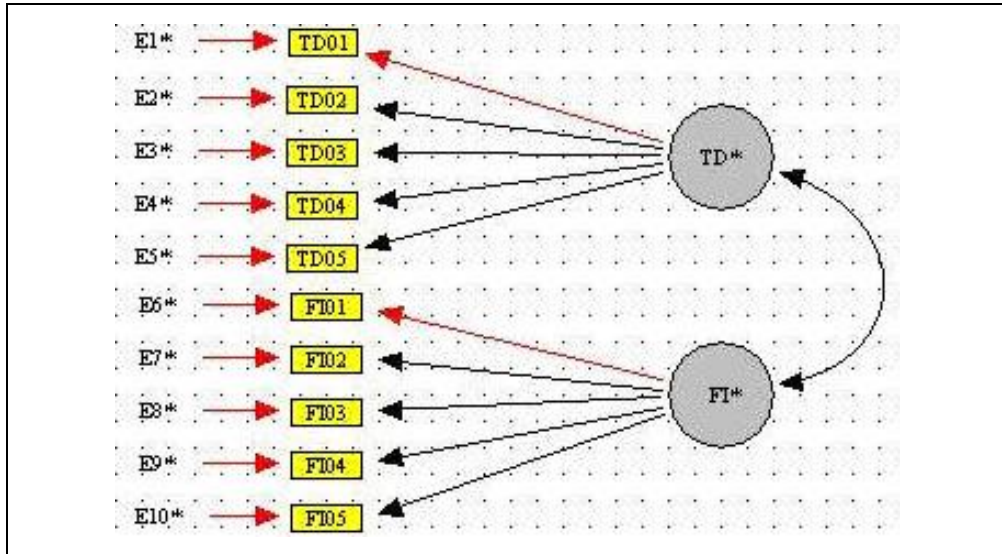
Figure A-11. CFA with Temporal Dissociation and Focused Immersion

Next, we run the constrained model and calculate the difference in χ^2. To fix the covariance at 1.0, we simply double-click on the covariance and select "Fixed Parameter" (see Figure A-12).

Figure A-12. Setting Covariance Between Factors to 1.0

Model 4: Parallel Model

We test the parallel model first. The parallel model is a superordinate model which constrains the factor loadings and residual variances to be equal. Before we can constrain the factor loadings and residual variances, we first diagram the second-order factor. We start by inserting the indicators and first-order factors.

Next, we assign the indicators to the factors. Then, we fix a parameter estimate to 1.0 for one indicator of each first-order factor (see Figure A-13).
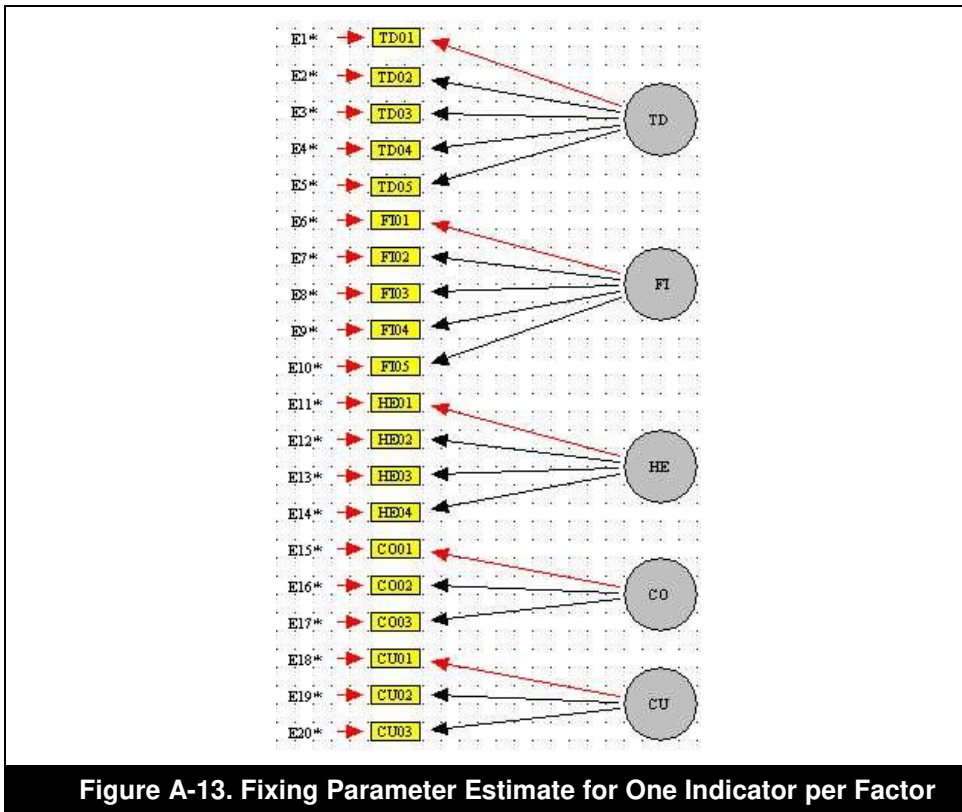
Figure A-13. Fixing Parameter Estimate for One Indicator per Factor

Next, we can introduce our second-order factor. We use the factor tool to insert another factor (see Figure A1), and then we draw reflective paths to each first-order factor. Next, it is necessary to set a scale for the multidimensional construct. This may be accomplished by fixing a path leading from the construct to 1.0 or by fixing the variance of the construct to 1.0, thereby standardizing the construct. To conduct statistical tests involving the multidimensional construct, we must obtain standard errors for paths leading to and from the construct, and these standard errors cannot be calculated for fixed paths. Hence, we set the scale of our cognitive absorption construct by fixing its variance to 1.0 (see Figure A-14).
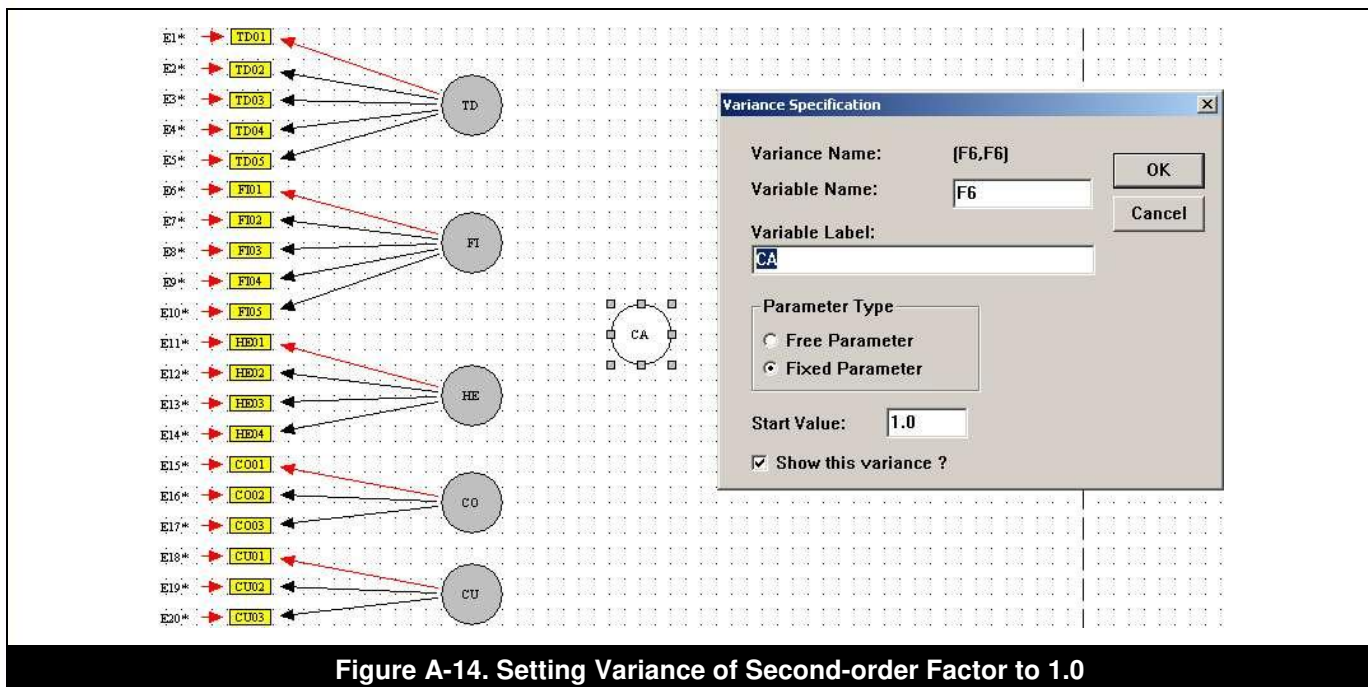
Figure A-14. Setting Variance of Second-order Factor to 1.0

We will use the factor tool to insert another latent factor, and then we will draw reflective paths to each first-order factor.
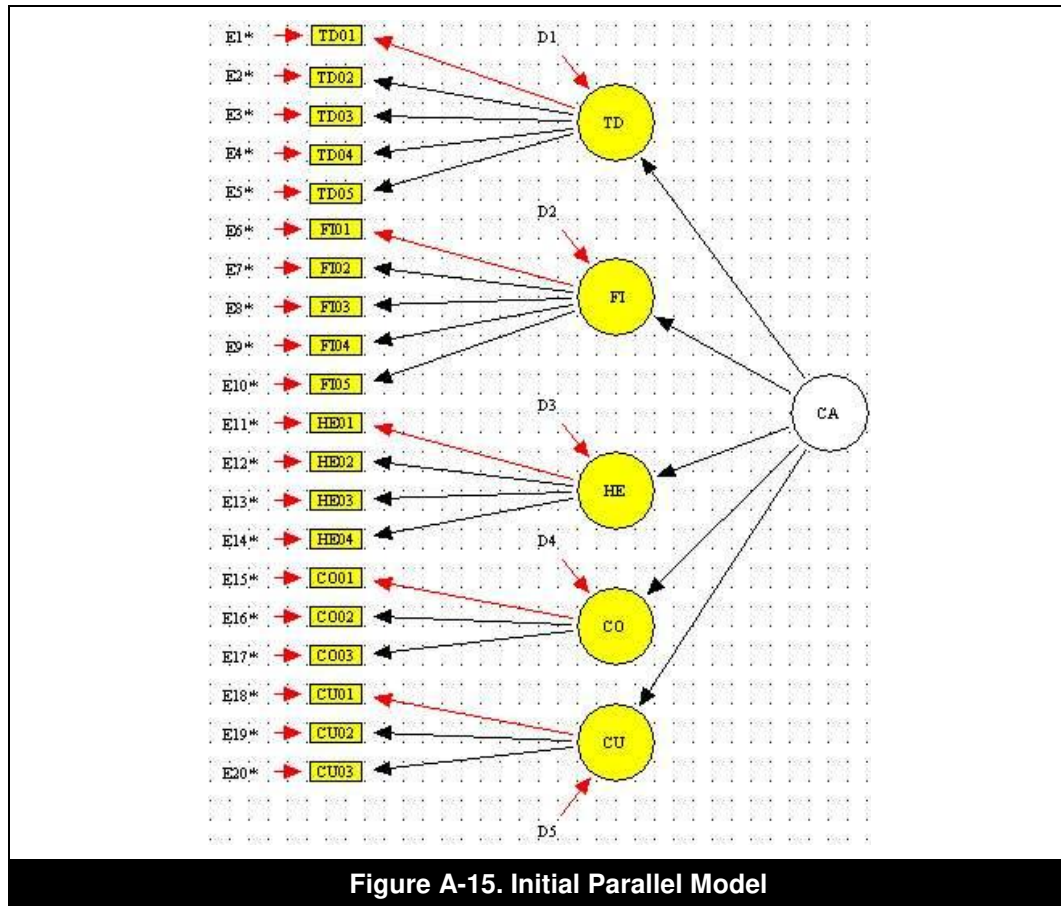
Figure A-15. Initial Parallel Model

Figure A-15 depicts our initial second-order model. In order to implement the constraints, we must first translate the diagram into the EQS command file. We do so by selecting "Build EQS" and clicking "Title/Specifications." After the EQS command file is generated, we implement the desired constraints into the command file. We select "Build EQS" and click "Constraints." Nest click constraints to open an additional window.

First, we constrain all factor-to-factor paths by checking the "Constrain all factor paths (F->F)" box. Then, we wish to constrain all of the residual variances as equal. To do this we select all of the residual variances (D1,D1 through D5,D5) and transfer them to the constraints by clicking the right button (see Figure A-16).
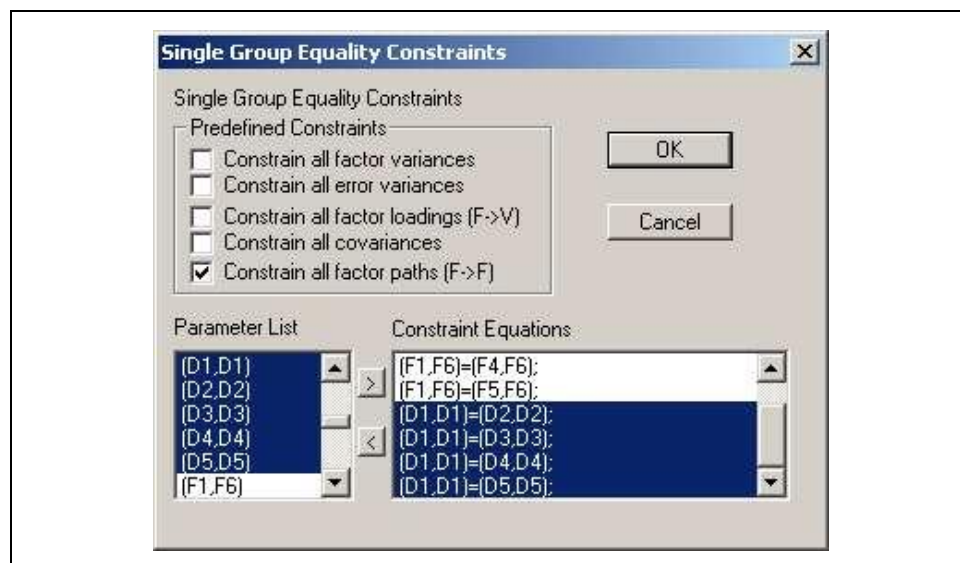
Figure A-16. Constraining Factor Paths and Residual Variances

Model 5: Tau Equivalent

To create this model, we construct it in the same manner as the parallel model, but we eliminate the residual variance constraints. We use the same model, but when we generate the model and implement constraints, we insert only factor-to-factor constraints. Figure A-17 depicts only factor-to-factor constraints.
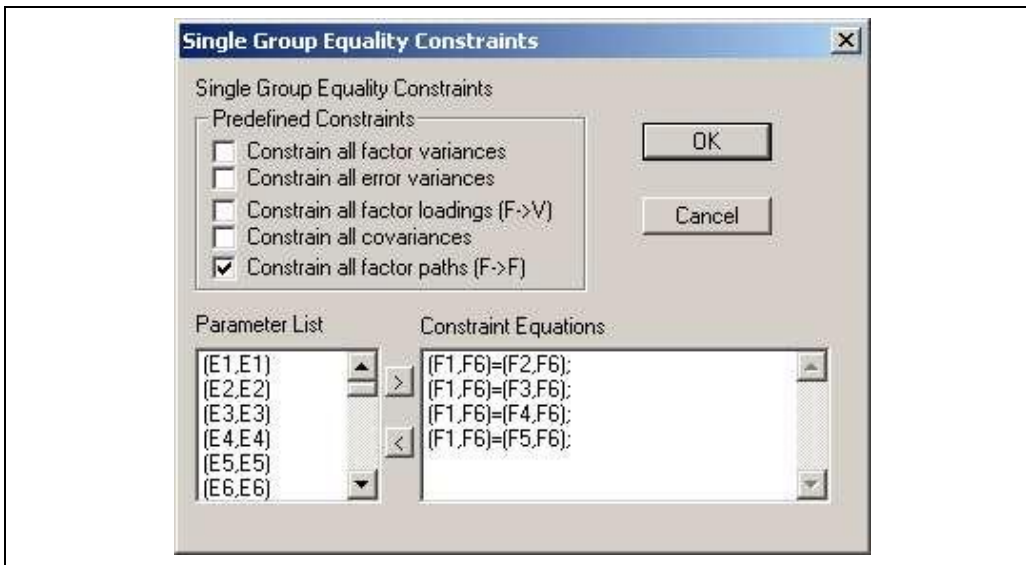
Figure A-17. Constraining Factor Paths

Model 6: Congeneric Model

The congeneric model is the same as the parallel and tau equivalent models with one exception: all constraints are removed. We simply build and run the superordinate model without any constraints imposed. Moreover, the congeneric model represents a standard second-order factor model [Rindskopf and Rose, 1988].

Structural Model

Having assessed the dimensionality, convergent validity, and discriminant validity of our superordinate construct, we can proceed to an analysis of the theoretical model proposed by Agarwal and Karahanna [2000].

We first select the model builder and commence with an empty diagram window. We then insert all of the indicators that we intend to use in the path model. We insert factors and assign indicators to the appropriate factor with reflective paths. Also, we fix one indicator at 1.0 for each first-order factor. And we fix the variance of the second-order factor (cognitive absorption) at 1.0. We then use the path tool to draw causal paths between the factors (see Figure A-1).

Figure A-18 depicts our structural model.

From here, we generate the EQS command file (see Appendix B for the command file) and select the appropriate analysis and output options. We set EQS to analyze the data using robust methods; we request a correlation matrix; and we run the structural model. The full model with standardized paths appears in Figure A-19.
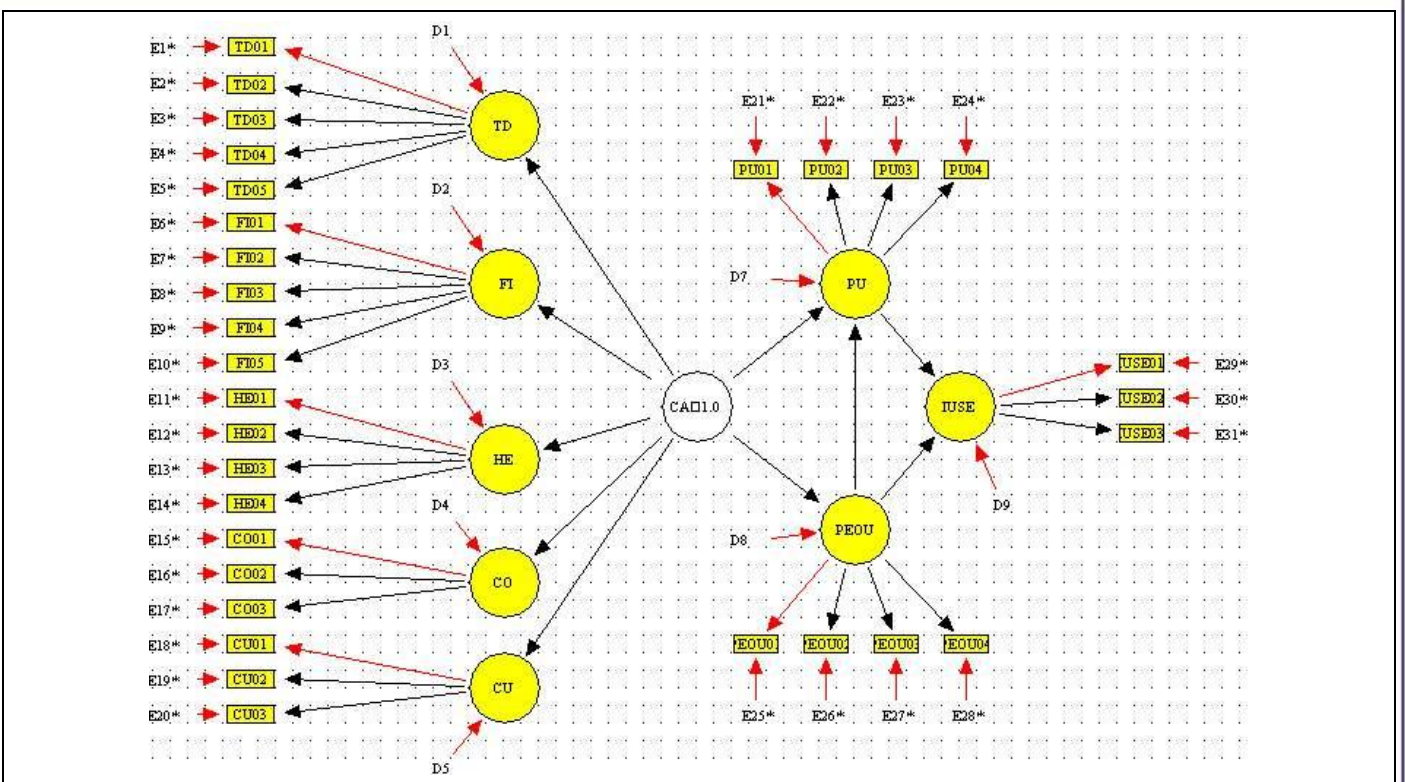
Figure A-18. Structural Model
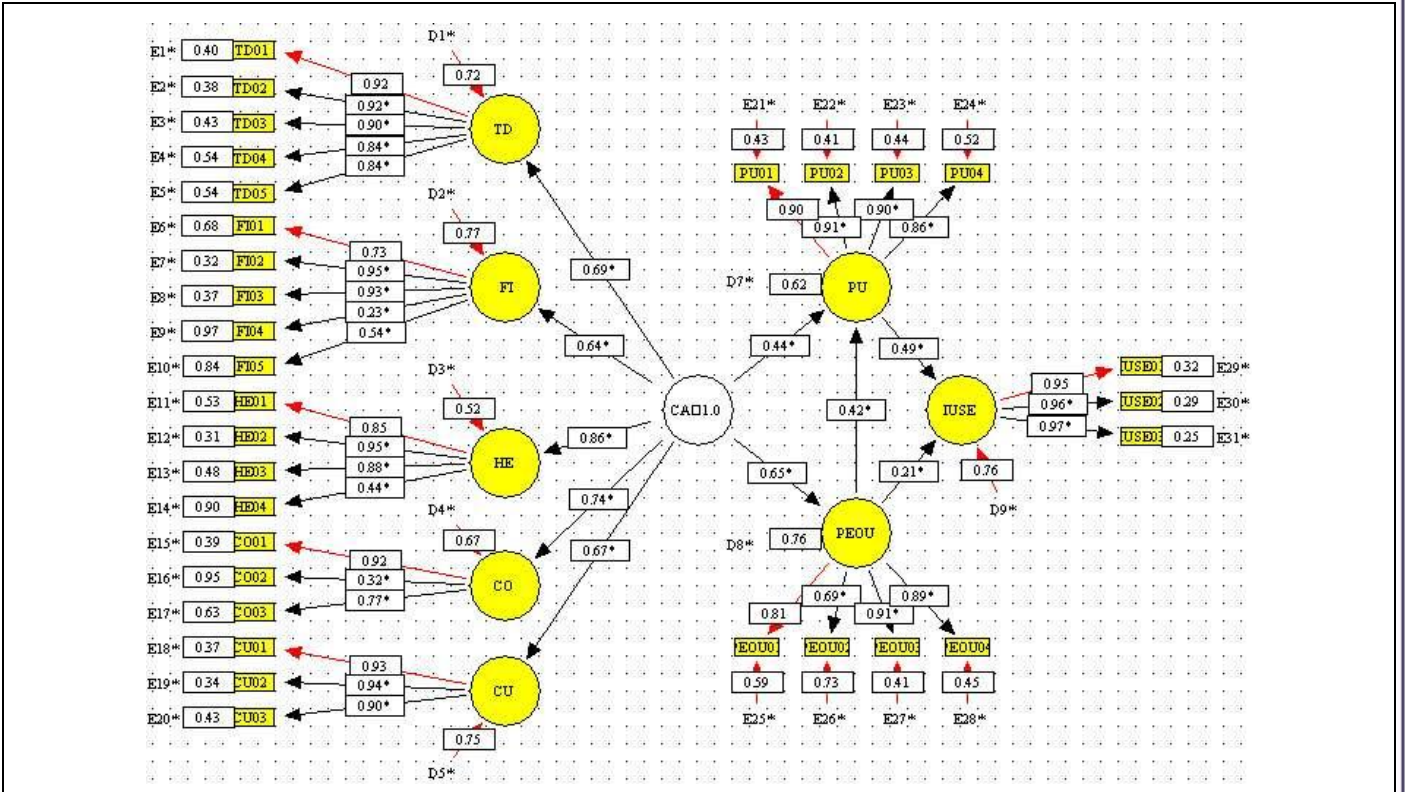
Figure A-19. Standardized Solution for Structural Model

APPENDIX B: EQS COMMAND FILE (STRUCTURAL MODEL)

```
/TITLE
Model built by EQS 6 for Windows

/SPECIFICATIONS
DATA='c:\research\multi\multidimensional-ca.ess';
VARIABLES=31; CASES=318;
METHOD=ML,ROBUST; ANALYSIS=COVARIANCE; MATRIX=RAW;

/LABELS
V1=TD01; V2=TD02; V3=TD03; V4=TD04; V5=TD05;
V6=FI01; V7=FI02; V8=FI03; V9=FI04; V10=FI05;
V11=HE01; V12=HE02; V13=HE03; V14=HE04; V15=CO01;
V16=CO02; V17=CO03; V18=CU01; V19=CU02; V20=CU03;
V21=PU01; V22=PU02; V23=PU03; V24=PU04; V25=PEOU01;
V26=PEOU02; V27=PEOU03; V28=PEOU04; V29=IUSE01; V30=IUSE02;
V31=IUSE03;

/EQUATIONS
V1  =    1F1 + E1;
V2  =    *F1 + E2;
V3  =    *F1 + E3;
V4  =    *F1 + E4;
V5  =    *F1 + E5;
V6  =    1F2 + E6;
V7  =    *F2 + E7;
V8  =    *F2 + E8;
V9  =    *F2 + E9;
V10 =    *F2 + E10;
V11 =    1F3 + E11;
V12 =    *F3 + E12;
V13 =    *F3 + E13;
V14 =    *F3 + E14;
V15 =    1F4 + E15;
V16 =    *F4 + E16;
V17 =    *F4 + E17;
V18 =    1F5 + E18;
V19 =    *F5 + E19;
V20 =    *F5 + E20;
V21 =    1F7 + E21;
V22 =    *F7 + E22;
V23 =    *F7 + E23;
V24 =    *F7 + E24;
V25 =    1F8 + E25;
V26 =    *F8 + E26;
V27 =    *F8 + E27;
V28 =    *F8 + E28;
V29 =    1F9 + E29;
V30 =    *F9 + E30;
V31 =    *F9 + E31;
F1  =    *F6 + D1;
F2  =    *F6 + D2;
F3  =    *F6 + D3;
F4  =    *F6 + D4;
F5  =    *F6 + D5;
F7  =    *F6 + *F8 + D7;
F8  =    *F6 + D8;
F9  =    *F7 + *F8 + D9;

/VARIANCES
 F6 = 1;
 E1 = *;
```

```
E2  =  *;
E3  =  *;
E4  =  *;
E5  =  *;
E6  =  *;
E7  =  *;
E8  =  *;
E9  =  *;
E10 = *;
E11 = *;
E12 = *;
E13 = *;
E14 = *;
E15 = *;
E16 = *;
E17 = *;
E18 = *;
E19 = *;
E20 = *;
E21 = *;
E22 = *;
E23 = *;
E24 = *;
E25 = *;
E26 = *;
E27 = *;
E28 = *;
E29 = *;
E30 = *;
E31 = *;
D1  =  *;
D2  =  *;
D3  =  *;
D4  =  *;
D5  =  *;
D7  =  *;
D8  =  *;
D9  =  *;

/COVARIANCES

/PRINT
FIT=ALL;
CORRELATION=YES;
TABLE=EQUATION;

/END
```

APPENDIX C: STEP-BY-STEP INSTRUCTIONS USING SMARTPLS

This software required calculating two measurement models, as well as a structural model. First, consistent with Agarwal and Karahanna [2000], we estimated a confirmatory factor analysis to confirm the dimensionality of the first-order constructs. Then, using the factor scores of CA's dimensions, we simultaneously estimated the measurement and structural model. Hence, our first step involved constructing a first-order measurement model (see Figure C-1).
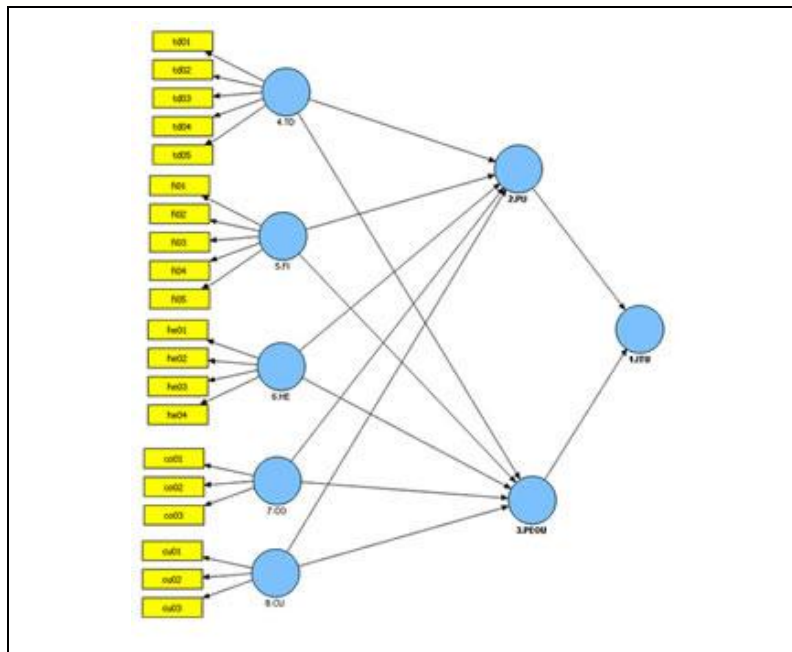
Figure C-1. Construct a Model in SmartPLS

Next, we click on "Calculate > PLS Algorithm."

To view our output, we click on "Report > Default Report."

After establishing discriminant validity in our measurement model, we turned to evaluating the structural model. To do so, we used the standardized latent variable scores for each of cognitive absorption's dimensions as indicators of the second-order construct. In SmartPLS, this requires creating a new data file that combines the latent variable scores estimated by the PLS algorithm with the raw data. To do so, we cut and pasted the scores from the SmartPLS default report into Excel. To access the scores, we selected the default report option in SmartPLS after running the PLS algorithm.

We copy and paste these scores into Microsoft Excel (see Figures C-2 and C-3).

Figure C-2. Copy Latent Variable Scores

AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM
iuse02	iuse03	1.ITU	2.PU	3.PEOU	4.TD	5.FI	6.HE	7.CO	8.CU
4	4	-1.8635	-3.1543	-2.9412	-3.8068	-2.8711	-2.5804	-2.541	-2.6507
7	7	0.8465	0.6913	0.8182	-0.5605	0.1065	-1.2347	1.4164	1.2568
7	7	0.8465	0.4525	-0.5393	-0.7981	-0.3589	0.008	1.1656	-0.2384
6	6	-0.0568	0.4433	-0.1216	-3.2997	0.3761	-3.0092	0.1331	-1.4353
7	7	0.8465	0.221	1.758	-1.6699	-2.2163	-0.5441	1.2034	-0.8375
6	7	0.5457	-2.6767	-1.8127	-2.5578	0.9076	-0.3464	-0.506	1.5563
6	6	-0.0568	0.6913	1.758	-3.1225	-1.73	-2.1396	1.1656	1.2568
5	5	-0.9601	0.6743	-1.5087	-2.7718	0.4448	-0.6185	-2.1501	0.3409
6	6	-0.0568	-0.0052	0.9029	-1.5256	-2.6146	-0.1033	-0.2603	0.0599
6	6	-0.3573	-0.9927	-0.8677	-0.865	-0.8833	-1.5978	-0.0799	0.0981
5	4	-1.8632	-0.7322	-0.3802	-2.0705	-1.3642	-2.113	-1.932	-1.4353
6	6	-0.0568	-0.0265	-0.3853	-1.1958	-1.0375	-0.2745	-0.007	-1.7534
7	7	0.8465	-0.5012	-1.2155	-2.0705	-2.2344	-1.9418	-0.8994	-1.4353
5	6	-0.9586	-0.5181	0.1221	-1.7264	-0.1648	-1.1587	-1.115	0.9573
5	5	1.2606	2.2008	0.6287	2.0771	0.4425	1.7827	1.5050	1.4252

Figure C-3. Paste Latent Variable Scores in Microsoft Excel

Following this, we save the Excel spreadsheet as a comma-separated value (.csv) file. The data must then be reloaded into a new project in SmartPLS. We then construct a new model using the latent variable scores as indicators of the multidimensional construct (see Figure C-4).
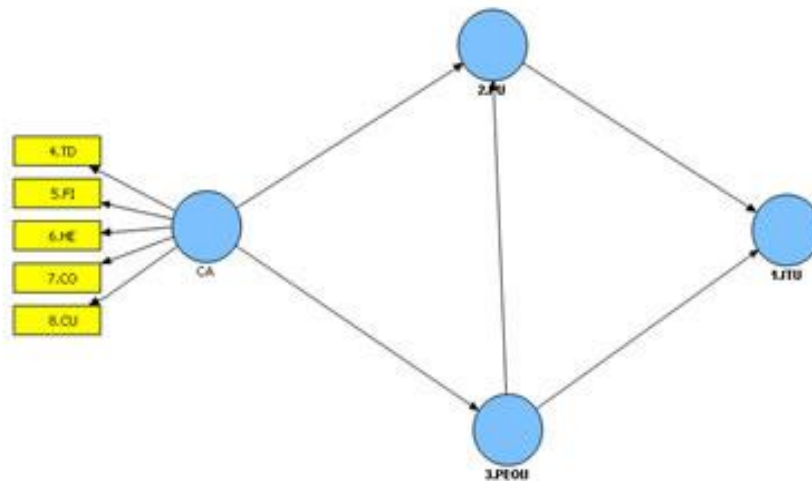
Figure C-4. Second-Order Factor Model

We execute the PLS algorithm again to generate results for our second-order factor model (see Figure C-5).
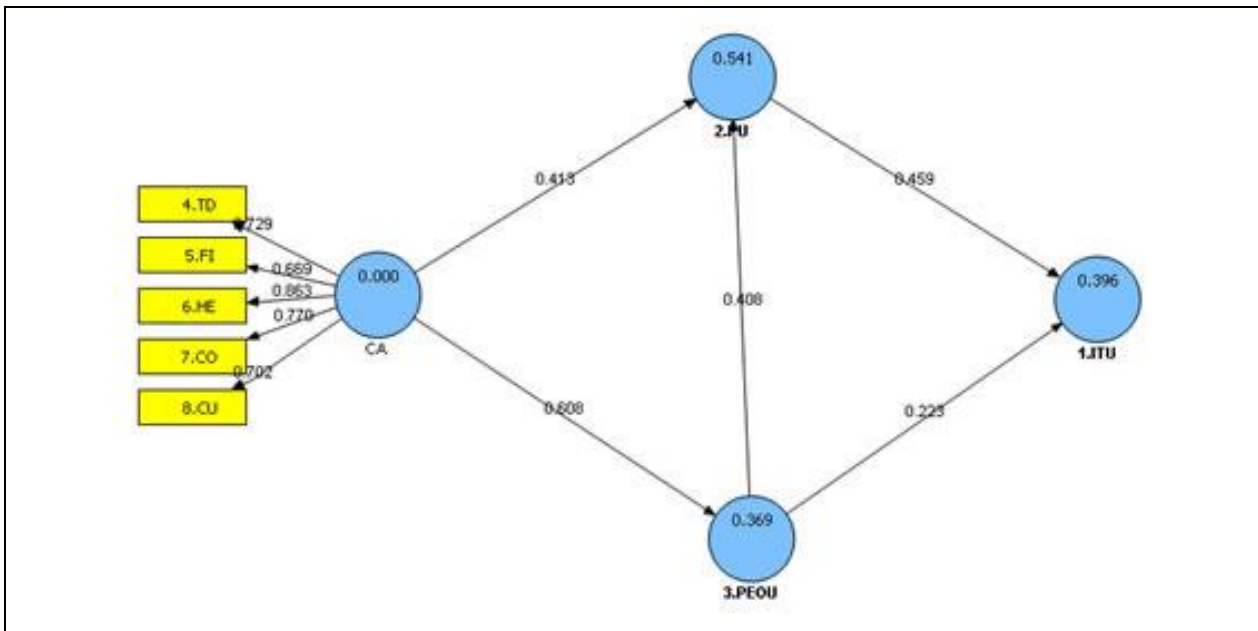
Figure C-5. Results for Second-Order Factor Model

We bootstrap the model by clicking on "Calculate > Bootstrapping." Figure C-6 depicts the results of our bootstrapped model.
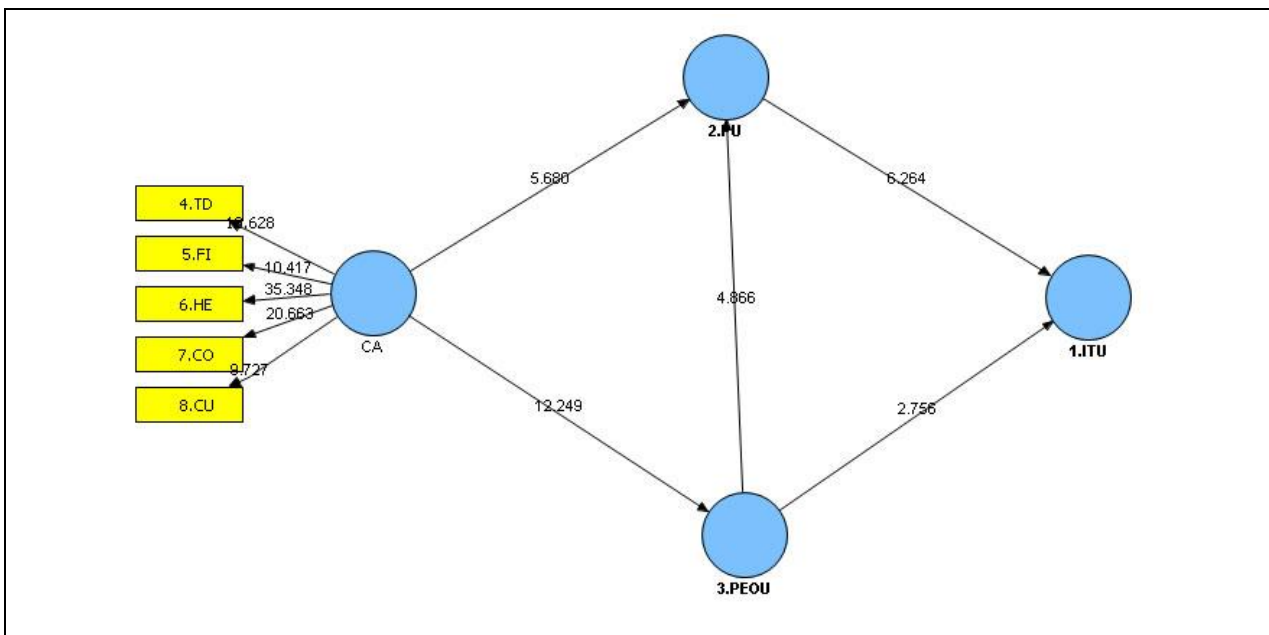
Figure C-6. Results of Bootstrapped Model

Following this, we generate the HTML report (see Figure C-7).

Table of contents (complete)

Bootstrapping

Bootstrapping

Outer Weights

	4.TD	5.FI	6.HE	7.CO	8.CU	iuse01
Sample 0	0.238103	0.230791	0.270871	0.284601	0.227972	0.330994
Sample 1	0.264584	0.250439	0.352526	0.310790	0.208811	0.338731

Figure C-7. HTML Report in SmartPLS

APPENDIX D: CONSTRUCT MEASURES, MEANS AND STANDARD DEVIATIONS*

Table D-1: Construct Measures, Means and Standard Deviations*		
Construct	Mean	S.D.
Temporal Dissociation		
Time appears to go by very quickly when I am using Internet Applications.	5.32	1.29
Sometimes I lose track of time when I am using Internet Applications.	5.40	1.26
Time flies when I am using Internet Applications.	5.35	1.26
Most times when I get on to Internet Applications, I end up spending more time than I had planned.	5.42	1.26
I often spend more time on Internet Applications than I had intended.	5.45	1.25
Focused Immersion		
I am able to block out most other distractions.	4.41	1.36
I am absorbed in what I am doing.	4.69	1.23
I am immersed in the task I am performing.	4.63	1.28
I get distracted by other attentions very easily.**	3.74	1.40
When using Internet Applications, my attention does not get diverted very easily.	4.12	1.36
Heightened Enjoyment		
I have fun interacting with Internet Applications.	5.06	1.17
Using Internet Applications provides me with a lot of enjoyment.	4.96	1.20
I enjoy using Internet Applications.	5.12	1.16
Using Internet Applications bores me.**	4.80	1.44
Control		
When using Internet Applications I feel in control.	4.94	1.21
I feel that I have no control over my interaction with Internet Applications.**	4.74	1.42
Internet Applications allow me to control my computer interaction.	4.87	1.09
Curiosity		
Using Internet Applications excites my curiosity.	4.63	1.16
Interacting with Internet Applications makes me curious.	4.63	1.16
Using Internet Applications arouses my imagination.	4.54	1.21
Perceived Usefulness		
Using Internet Applications helps me to accomplish tasks more quickly.	5.35	1.18
Using Internet Applications improves the quality of the work I do.	5.30	1.15
Using Internet Applications gives me greater control over my work.	5.19	1.13
Using Internet Applications enhances my effectiveness in my work.	5.28	1.07
Perceived Ease of Use		
My interaction with Internet Applications is clear and understandable.	5.19	1.22
Interacting with Internet Applications does not require a lot of mental effort.	4.89	1.25
I find Internet Applications to be easy to use.	5.23	1.19
I find it easy to get Internet Applications to do what I want them to do.	5.13	1.20
Intention to Use		
I intend to use Internet Applications in the future.	6.04	1.14
I predict I would use Internet Applications in the future.	6.06	1.15
I plan to use Internet Applications in the future.	6.09	1.13
* All items were measured with a 1. Strongly Disagree—7. Strongly Agree response format.		
** = reverse coded		
Item Correlation Matrix can be downloaded at www.usf-research.org/CAIS-Wright.		

ABOUT THE AUTHORS

Ryan T. Wright is an assistant professor of management information systems at University of Massachusetts Amherst. He holds a Ph.D. from Washington State University in Management Information Systems and an MBA and Bachelor of Science in Business from the University of Montana. Ryan's research interests take a behavioral approach to understanding how current technologies can be used to enable secure and efficient e-business transactions. He is published in *MIS Quarterly*, *Journal of Management Information Systems*, *Communications of the Association for Information Systems*, and other peer-reviewed journals. Ryan also is involved in information systems education efforts, including serving on the task force designing IS 2010 Undergraduate Model Curriculum.

Damon E. Campbell is an assistant professor of management information systems in the Else School of Management at Millsaps College. He holds a PhD and MBA from Washington State University. His primary research interests include e-commerce, human computer interaction, and interface design. He has published research in *Decision Sciences*, the *Journal of the Association for Information Systems*, and *AIS Transactions on Human-Computer Interaction*, as well as other referred journals and conference proceedings.

Jason Bennett Thatcher received the B.A. degree in history and political science from the University of Utah, Salt Lake City, in 1994 and 1999, respectively; the M.P.A. degree from Askew School of Public Administration and Policy, Florida State University, Tallahassee, in 1999; and the Ph.D. degree in business administration from the College of Business, Florida State University, in 2002. He is currently an Associate Professor in the Department of Management, Clemson University, Clemson, SC. His current research interests include examining the influence of individual beliefs and characteristics on the use of information technology, and also include strategic and human resource management issues related to the application of technologies in organizations. His work appears in the *MIS Quarterly*, *Journal of Management Information Systems*, *IEEE Transactions on Engineering Management, American Review of Public Administration,* and *Journal of Applied Psychology.*

Nicholas Roberts is an assistant professor in the Johnson College of Business and Economics at the University of South Carolina Upstate. He received his Ph.D. in Management from Clemson University. His current research interests include IT business value and health IT. His work has appeared or is forthcoming in *MIS Quarterly, Journal of Management Information Systems, European Journal of Information Systems,* and *IEEE Transactions on Engineering Management.*