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Ghiyoung Im
Clark Atlanta University, ghiyoung@gmail.com

Jijie Wang
Georgia State University
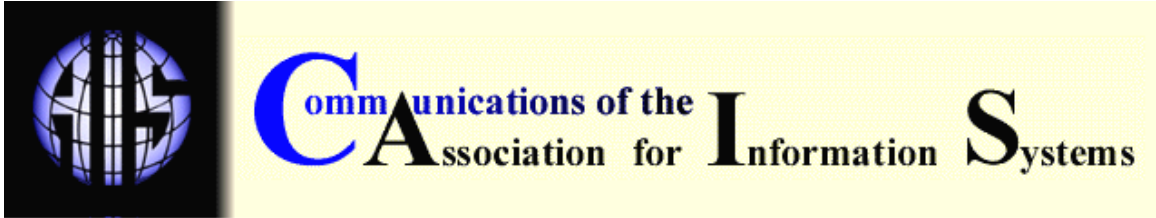
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A TETRAD-BASED APPROACH FOR THEORY DEVELOPMENT IN INFORMATION SYSTEMS RESEARCH

Ghiyoung Im
Clark Atlanta University
ghiyoung@gmail.com

Jijie Wang
Georgia State University

ABSTRACT

Theory development and theory testing are two primary processes in social science research. Statistical methods and tools are used in various stages of these processes. Information systems researchers have employed many statistical methods and tools for theory testing. However, very few statistical approaches are known to help researchers with theory development. In this paper, we introduce TETRAD as a powerful approach to aid researchers in developing and discovering new theoretical relationships. We illustrate the TETRAD approach by re-analyzing data from two articles published in premier information systems journals. The results from the previous examples demonstrate that TETRAD is a useful tool for uncovering potential theoretical relationships, especially when prior knowledge of underlying theory bases is lacking. We demonstrate that TETRAD is an effective and powerful statistical tool that can assist researchers in the iterative process of theory development.

Keywords: TETRAD, Theory Development

I. INTRODUCTION

Researchers in the information systems (IS) field have striven to achieve theoretical maturity and methodological rigor. Historically, IS has been criticized for a lack of theories and for methodological weaknesses [Lee et al. 1997]. Over two decades ago, some researchers suggested that IS had no established theories that could be deployed in confirmatory research and therefore should focus on exploratory research [Kauber 1986; Klein and Lyytinen 1985]. With persistent efforts among IS researchers, the field has accumulated a considerable amount of knowledge concerning the concepts, theories, and processes surrounding IS phenomena [Baskerville and Myers 2002]. In recent years, the creation of such knowledge has led to a vibrant debate on the identity of the field [King and Lyytinen 2006]. Whether the argument is calling for consensus around a distinct, core paradigm [Benbasat and Zmud 2003] or for a flexible identity [Robey 2003], this kind of debate reflects the theoretical maturity of the field. Researchers have also called for increased methodological rigor in validating IS research instruments [Straub 1989]. Other studies have made considerable improvement in validation practices for quantitative and positivistic IS research [Boudreau et al. 2001].

Despite such theoretical and methodological progress, the field has not paid proper attention to improving theory development. As a social science discipline, the IS field employs exploratory and confirmatory research to develop theoretical models. In exploratory research, facts, ideas, patterns, or hypotheses are examined to make a theoretical case in an area where little information about a phenomenon exists. Confirmatory research focuses on testing theoretical models developed through rigorous processes of theory development. One implicit, but important, practice of theory development across exploratory and confirmatory research is that researchers, more often than not, engage in iterative theory development processes in order to achieve the final theoretical model. This practice is particularly salient in exploratory research and the early stages of confirmatory research. Such a practice is deemed necessary because, in exploratory research, relationships between constructs are unknown and, in the early stages of confirmatory research, our understanding of the proposed theoretical model is not clear or the proposed theoretical model is not strong. The iterative development of the Technology Acceptance Model (TAM) [Davis 1989] provides an illustration of this phenomenon. TAM was based on a prior theory called Theory of Reasoned Action [Fishbein and Ajzen 1975]. During its development process, Davis eliminated certain variables and added new relationships to explain individuals' decision-making about technology acceptance in a parsimonious manner. Thus even a well-known theory in the field went through an interactive trial and error or test-retest process in its early stages. During the iterative process of theory development, researchers have relied on a variety of statistical approaches such as comparing R^2s among alternative models in regression and relying on modification indices for a better fit in structural equation modeling (SEM) applications, for example. Such approaches are ad hoc and may end up with a local search, ignoring adjacent search spaces that may contain models that are better supported empirically.

In this article, we introduce TETRAD as a tool to assist in the process of iterative theory development. Iterative theory development processes are essential and important, particularly in exploratory research and the early stages of confirmatory research. The TETRAD-based approach is a bottom-up data-driven exploration for theory development that is useful when the phenomenon under investigation is not well known to the researcher. Often during the early stages, researchers do not have a good theory to specify a "unique" plausible model, theoretical knowledge is incomplete, or theoretical knowledge does not lead to a unique model specification. Thus, researchers typically rely on iterative processes for theory refinement such as identifying plausible models, comparing them, and selecting the best model. The TETRAD-based approach can be helpful in searching the space for models about which the researcher is uncertain and provide equivalent models for researchers to evaluate.[1]

Although Lee et al. [1997] discussed the necessity of building richer models using TETRAD at the exploratory stage of IS research, their work has not been followed up in the field. First, most IS researchers are concerned about testing their models in a confirmatory manner. Thus, using a method like TETRAD for exploratory analyses has a smaller role to play in the field. Second, it is likely that IS researchers are not aware of the existence of TETRAD as a proper method for exploratory analyses. A group of philosophers at Carnegie-Mellon University developed TETRAD in the 1980s and their ideas materialized as readily available software.[2] The software is free of charge, easy to use (especially version 4 with the introduction of a graphical user interface), and easy to learn. It has flexible structures for developing models and thus is useful for revealing relationships among constructs in unexplored problem areas. Lastly, some IS researchers may still have reservations about using TETRAD because they are worried about capitalizing on

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[1] Let's take an example. Suppose that we have a covariance data for six variables. We can have 4^{15} different theories of the causal dependencies among the six variables. If this number is not trimmed using prior knowledge, it will be a daunting task to select a few plausible models [Faust 1984]. Statistical tools can be quite helpful in selecting the models in such a case, and can do as good job as a causal theory does [Wood 1998].

[2] TETRAD is available at http://www.phil.cmu.edu/projects/tetrad/.

chance by using a method that belongs in the data mining tradition. As discussed later in this paper, TETRAD can incorporate background knowledge (e.g., known causal relationships among the constructs and time ordering among the constructs) into models to constrain the search space of the TETRAD program. Thus, researchers can prevent their use of TETRAD from becoming a fishing expedition and identify models consistent with the background knowledge they have.

In this research, we describe the underlying principles of TETRAD and demonstrate its usefulness after re-analyzing data from two articles published in premier IS journals. The philosophy, objective, algorithms, and functionality of TETRAD are quite different from those in traditional analyses such as partial least squares (PLS) and covariance-based structural equation modeling. Therefore, when applied at early stages of theory development, TETRAD may result in different findings from those via the traditional analyses. The creative tension between the results will be resolved after several rounds of iteration, leading to better-specified and more reliable understanding of the phenomenon. We hope that TETRAD plays a more prominent role during the discovery process of developing theoretical models in IS research than at present.

The organization of the paper is as follows: In section 2, we discuss statistical tools for theory development and the origin, assumptions, and algorithms of TETRAD. In section 3, we re-analyze data obtained from two published articles using TETRAD. In section 4, we discuss TETRAD's strengths and weaknesses. Section 5 outlines our conclusion.

II. THEORY DEVELOPMENT IN INFORMATION SYSTEMS

In this section, we describe the process of model specification and the complexity involved in selecting a model with solid theoretical foundations for social science research. Then we introduce the application and importance of a statistical tool such as TETRAD to complement the bounded cognitive capabilities of human beings during model specification processes.

STATISTICAL TOOLS FOR THEORY DEVELOPMENT

Quantitative and positivistic IS research consists of two stages: theory development and theory testing. At the theory development stage, researchers identify constructs and variables (operationalization of constructs), and build relationships among the identified constructs. First, the identified constructs are validated using statistical tests for reliability and construct validity. In addition, the construct scope must be sufficiently defined. The construct must sufficiently reflect the domain of the phenomenon, and the variables in turn must sufficiently reflect the domain of the construct. Lack of content validity in constructs limits the generalizability of a theory. Second, the logical linkages among the constructs are evaluated. The antecedent and the consequence must not be tautological and the nature of the relationship must be specified as necessary, sufficient, or necessary and sufficient. The assumptions, scope, and parsimony of the research model must be evaluated [Bacharach 1989]. At the theory testing stage, the relationships between constructs (i.e., hypotheses) are tested, and model parameters are estimated.

At the theory development stage, researchers can construct a model that has well-defined constructs with linkages among the constructs that are sufficiently justified based on existing knowledge. When the phenomenon is lesser-known or when multiple interpretations are possible, researchers cannot justify a single model by ruling out all the other possible alternative models solely based on existing background knowledge. Researchers may be faced with plausible alternatives to a given model, which may offer conclusions that lead to very different implications for a given problem. Therefore, the researcher usually engages in some degree of exploration to create the model. Given that this exploratory analysis is very complicated and requires a certain amount of subjectivity, statistical tools can be instrumental in helping overcome the limits of human judgment [Meehl 1954; Wood 1998].

THE TETRAD APPROACH

Background

The goal of TETRAD is to discover a set of causal models that are consistent with correlational data. Its techniques belong to the field known as "knowledge discovery in databases" or "data mining" [Frawley et al. 1991], and follow in the tradition of work on automated discovery by Simon, Buchanan, Blum, and others (see Lindsay et al. [1980] as an example). Contrary to most other SEM techniques that use data to infer a model's parameter values, TETRAD applies logical rigor and mathematical precision to the problem of using data and background knowledge to make inferences about model specification. If general assumptions (e.g., multivariate normality) are satisfied and the substantive assumptions (e.g., statistical constraints in the population) made by the researcher are correct, TETRAD can generate a set of models consistent with the data provided [Scheines et al. 1997].

TETRAD was developed by a group of philosophers at Carnegie-Mellon University, including Peter Spirtes, Clark Glymour, Richard Scheines, and Kevin Kelly [Spirtes 2001]. TETRAD represents causal relationships implicit in a model as a directed acyclic graph (DAG), which is similar to a path or structural model in structural equation modeling. Drawing on graph theory and probability analysis, TETRAD's creators have developed algorithms for discovery and prediction that systematize the procedures for uncovering causal models. TETRAD tries to find all possible models that explain the data. Using this type of exploratory tool prevents reliance on the common practice of focusing on a unique model without exploring alternatives.

It is important to note that, following the tradition of Wright [1921] and Haavelmo [1943], TETRAD researchers argue that researchers can "always" give causal interpretations to identified structural coefficients [Pearl 1998]. They argue that, mathematically, variable X is a *probabilistic cause* of variable Y if $P(y \mid do(x)) \neq P(y)$ for some values x and y, where P is a probability function. The do(x) stands for doing X = x in an ideal experiment, where X, and X alone, is manipulated, and not any other variables in the model. That is, if the probability of an event y, P(y), changes after another event, x, has occurred, and is represented as $P(y \mid do(x))$, then X is said to be a probabilistic cause of variable Y. If not, they are said to be independent. Their theory of probabilistic causality is built upon the following assumptions: Causal Independence, which means that if X does not cause Y and Y does not cause X, and X and Y have no common antecedent, then X and Y are independent; Causal Markov, which is about the way causation and probability (independence relations) are connected; and Faithfulness, which is designed to eliminate independence relations that rely on peculiar coincidences [Scheines 1997]. According to TETRAD researchers, researchers can make causal claims from statistical data as long as these assumptions hold [Pearl 2000; Scheines 1997]. The bottom line is that their probabilistic causality is defined via statistical independence, and their efforts are focused on clear identification of statistical independence.[3] [4]

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[3] The crux of understanding probabilistic causality by TETRAD researchers is comprehending the underlying assumptions of their theory. We refer readers to Scheines [1997] and Pearl [2000] for detailed explanations of these assumptions and for a formal proof.

[4] To comply with TETRAD researchers' theory, this article uses the term "causality" as defined earlier. As is common practice in the IS field, we do not endorse their assumptions and thus causality claims. However, it is important to note that their theory is "about the inferential effect of a variety of assumptions far more than it is an endorsement of particular assumptions" [Scheines 1997, p. 199]. Thus, we should focus on what can be learned about models via TETRAD, not whether we can make causal claims from statistical data.

Correlation Constraints

When using TETRAD to search for causal models, researchers need to provide a correlation matrix of the sample data and then make some key assumptions. One necessary assumption is whether "causal sufficiency" holds up – meaning whether the causal structure of the constructs is explained purely by relationships among the constructs without additional latent or unobserved constructs [Spirtes 2001].

TETRAD uses two correlation constraints to search for recursive models (i.e., models without reciprocal relations or feedback loops) based on background knowledge and the types of recursive models sought: vanishing partial correlation constraints and vanishing tetrad constraints [Rigdon 2005; Scheines et al. 1998b]. First, *vanishing (partial) correlation constraints* construct structural models that have the same set of conditional independence relationships among the variables and are compatible with background knowledge. A test of zero correlation or zero partial correlation is equivalent to a test of independence or conditional independence. That is, $\rho_{BC.A} = 0$ $\Leftrightarrow B \perp\!\!\!\perp C \mid A$. In this expression, the former expresses the partial correlation of B and C controlling for A and the latter describes B as independent of C, conditional on A. Such tests can be used to decide conditional independence among two variables. If A, B, and C are mutually correlated variables, $\rho_{BC.A} = 0$ suggests two possibilities. One is that A directly or indirectly predicts both B and C; the other is that the relationship between B and C is fully mediated by A (Figure 1) [Rigdon 2005b; Spirtes 2001].

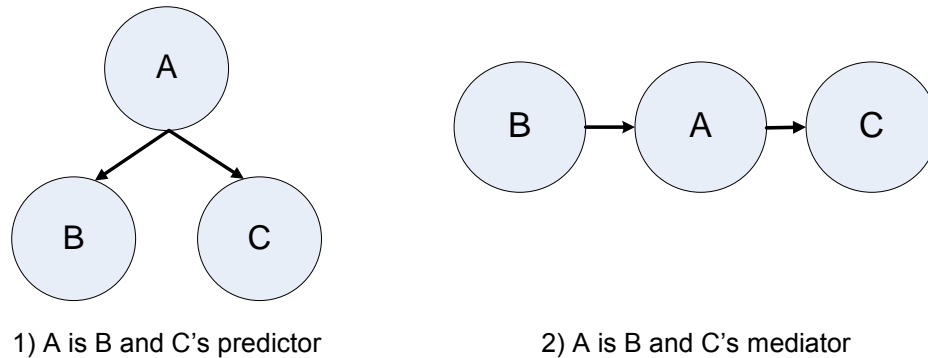1) A is B and C's predictor   2) A is B and C's mediator

Figure 1. Two Possible Models When $\rho_{BC.A} = 0$

Next, if the researcher does not assume causal sufficiency, he or she can examine *vanishing tetrad constraints* to search for latent variables. A tetrad is defined as the difference between the products of two pairs of covariances or correlations. For a set of four variables, we can have three tetrads:

$$\tau_{ABCD} = \rho_{AB}\, \rho_{CD} - \rho_{AC}\, \rho_{BD}$$

$$\tau_{ACDB} = \rho_{AC}\, \rho_{DB} - \rho_{AD}\, \rho_{CB}$$

$$\tau_{ADBC} = \rho_{AD}\, \rho_{BC} - \rho_{AB}\, \rho_{DC.}$$

A vanishing tetrad means $\tau_{ABCD} = 0$. Based on the assumption of multivariate normal, TETRAD uses the Wishart [1928] statistical test (the null hypothesis being $\tau_{ABCD} = 0$) to calculate the set of tetrad differences that vanish statistically. Different latent variable models may show the same pattern of vanishing tetrad differences (Figure 2). However, with enough prior knowledge and theoretical criteria, the researcher should be able to choose one model over the alternatives [Rigdon 2005b].
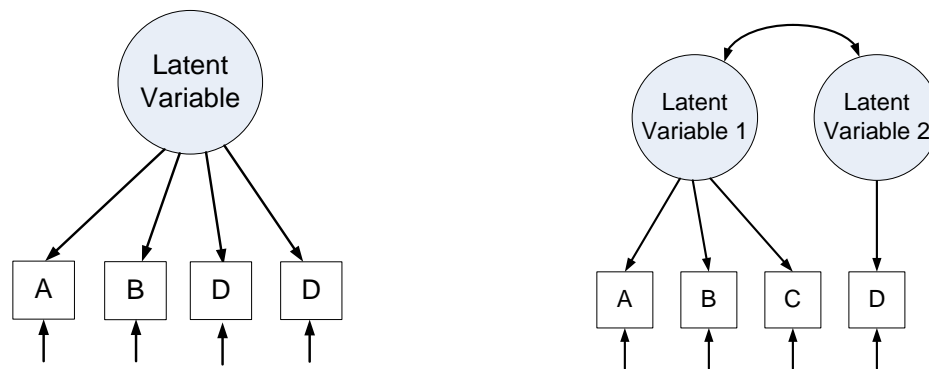
Figure 2. Different Latent Variable Models with the Same Pattern of Vanishing Tetrad Differences (All Tetrads Vanish) (adopted from Rigdon [2005b])

The above constraints are used to generate a pattern that is consistent with the data. The researcher must specify a significance level (i.e., α) to search for zero partials or vanishing tetrad differences. The statistical significance of a given statistic is tested as follows:

H0: Statistic is 0 in the population

H1: Statistic is not 0 in the population

A moderate α (0.1 or 0.2) will result in a highly saturated pattern with many undirected paths or edges (i.e., directional paths whose direction is unknown), while an extreme α (0.05 or 0.01) will generate a sparse pattern [Rigdon 2005b]. TETRAD does not have any specific requirement for sample size, but works best when the network is sparse and sample size is large. When sample size is small (large), we can determine the results by setting a moderate (extreme) α. Determining the α level is a key choice and users should use their own discretion in choosing it and using sample size as an input. If the model is very sparse, it may not be very useful. Thus, users may want to start with a saturated model by having a moderate α.

- Sample size 100 or smaller: Set α = .2

- Sample size 100 to 300: Set α =.1

- Larger samples: Set α = .05 or smaller.

Comparing TETRAD with PLS and SEM

Covariance-based SEM is commonly used for theory confirmation in IS research. It compares the covariance structure fit of the researcher's model to a best possible fit covariance structure. Its objective is to show that the operationalization of the theory being examined corroborates, and is not disconfirmed, by the data [Gefen et al. 2000]. Therefore, covariance-based SEM should be used when the theory is strong and the sample size is large. It should not be used when the research is exploratory (see Table 1 for comparisons with other techniques).

Researchers have also embraced PLS as a powerful tool that is applicable at various stages of a study. This recognition is partly caused by its less stringent requirements (i.e., arbitrary distributions and weak theory) as well as its capability to assess structural and measurement models simultaneously [Chin 1998]. Despite such advantages, it appears that PLS has weaknesses in meeting the diverse demands of a researcher's exploratory analyses [Marcoulides and Saunders 2006]. Specifically, it falls short in finding alternative models during the theory development process (see Rigdon [2005b] for details on TETRAD and PLS).

First, PLS tests a model in a confirmatory manner and does not have mechanisms to explore diverse causal structures consistent with the input data. Although some researchers suggest that PLS is useful for exploratory analysis, the tool simply assesses whether the data fits the model using least squares regressions to maximize prediction of dependent variables, that is, R^2. Because PLS is used to derive parameter estimates, it does not make use of all the information from the data.

Table 1. Comparison between TETRAD, PLS, and Covariance-Based SEM

	TETRAD	**PLS**	**Covariance-based SEM**
Goals	- Discover a set of causal models that are consistent with input	- Maximize prediction of dependent variables	- Show that the data corroborate the operationalization of the theory being examined
Conditions for use	- Multivariate normality - Theory not required - Performs best when the network is sparse and sample size is large	- Arbitrary distributions - Weak theory	- Multivariate normality required if estimation is through maximum likelihood - Strong theory base - Sample size at least 100-150
Characteristics	- Data to model approach - Accommodate only recursive relationships	- Data-rich but theory-primitive - Consistency at large - Bootstrapped or jackknifed standard errors	- Data-rich and theory sound
Execution	- Partial correlations - Vanishing tetrad differences	- Iterative parameter estimation via a series of regressions	- Compare the covariance structure fit of the researcher's model to a best possible fit covariance structure
Weaknesses	- Conditional independence tests when distributional assumptions are not met - *Purify and MIMBuild* does not incorporate background knowledge - Interpretation of TETRAD-generated latent constructs	- Does not produce overall test statistics - Uses arbitrary rules for estimation and testing - Cannot incorporate correlated error terms, and cross-loadings	- Not appropriate for exploratory purposes
Software products	- TETRAD	- PLS-Graph, SmartPLS	- LISREL, EQS, AMOS, MPLUS

Second, PLS does not require any distributional assumption, and thus cannot provide any test statistic to evaluate model quality. Bootstrapping and jackknifing can be used for model improvement. However, the inability of PLS to provide test statistics when examining the entire model becomes critical when a hypothesized path is not supported and model improvement is warranted. In the absence of any reliable test statistics, researchers may "capitalize on chance" in an attempt to create a better model.

Last, PLS is limited in its ability to aid in refining measurement models because it cannot incorporate correlated error terms or account for cross-loadings of indicators to multiple latent constructs. It computes latent variable scores without any measurement model assumptions [Sampson and Bookstein 2005]. Latent constructs in PLS have exact values that are calculated

by ordinary linear combinations of the observed data. For exploratory analyses, researchers may need to redefine their structural and measurement models based on patterns of correlated error terms, and loadings and cross-loadings of indicators to latent variables.

USE OF TETRAD FOR THEORY DEVELOPMENT

TETRAD aims to identify a class of plausible models, not a single correct model, by using vanishing partial correlation constraints and vanishing tetrad constraints. This feature helps researchers think beyond a given model, if any, by casting a wider net during the theory development stage. In a given model, researchers can construct alternative models by adding or deleting paths. This strategy, however, may lead to missing a whole set of models that are not nested within a given model. Eventually, researchers may obtain models which have a better fit even though their theoretical validity is justified ex post [Rigdon 2005a].

TETRAD can play a more important role in the discovery process of model development. In this process, researchers often iterate between theories and data in order to establish a model that is both theoretically sound and empirically validated. Practically, TETRAD can be used as the front end of the traditional analysis such as PLS and SEM. TETRAD can generate a collection of possible theoretical models, which can then be used as input for PLS and SEM for parameter estimations. TETRAD operates under the assumption of multivariate normality of observed indicators. This assumption enables statistical tests whose results are used to establish convergent and construct validity of measurement models. Researchers can limit potential models by including background knowledge to ensure that TETRAD only derives theoretically plausible models. Emerging information, such as patterns of correlated error terms, loadings, and cross-loadings of indicators to latent constructs as well as generated latent constructs based on the indicators, can be utilized to define and redefine measurement and structural models. Thus, TETRAD provides more flexible structures to identify and refine measurement and structural models than exploratory factor analysis. TETRAD tends to uncover a known structure among variables better than exploratory factor analysis does [Mulaik 2005].

Researchers can take advantage of the path searching algorithms of existing SEM applications (e.g., modification index in LISREL and the Lagrange Multiplier statistic in EQS) to derive a set of correct models from a given start. The algorithms use a form of stepwise search, which is an extension of a problematic strategy in stepwise regression. The algorithms allow for incremental change in a given model based on some criterion. However, this stepwise approach does not guarantee the correct model because the approach entails a special relationship between the current model and the correct model. Thus, the correct model shares the same errors or limitations with the current model [Rigdon, 2002]. It is also likely that researchers miss a whole set of models that are not connected to a given model.

III. EXAMPLES OF TETRAD ANALYSIS

To demonstrate the usefulness of TETRAD, we selected two articles published in the IS field, ran TETRAD, and compared the TETRAD-generated results with the reported results.[5] The two articles were chosen because a correlation matrix at the item-level is available for analysis. In addition, these articles involve exploration in testing new variables (i.e., trust and IT-enabled institutional mechanisms) in an e-commerce context. We used TETRAD version 3 for data analyses and LISREL 8.7 for obtaining parameter estimates of the models derived by TETRAD.

Appendix A describes the search algorithms (Build, Purify, and MIMBuild) in TETRAD 3 in detail. Purify is used to establish construct validity of measurement models, and MIMbuild to test structural models based on input measurement models. Build is employed to test relationships

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[5] The application of TETRAD requires multinomial normality. This condition could not be confirmed in the two articles due to a lack of information.

between indicators, between latent constructs, and among indicators across latent constructs, and can incorporate background knowledge. Overall, Purify and Build test for measurement models, and MIMBuild and Build establish structural models. We can start with Purify to establish measurement models, then use MIMbuild or Build to ascertain structural models. It is important to note that we can change the output by varying the significance level, which leads to adding/pruning items as well as paths.

EXAMPLE 1: GEFEN, KARAHANNA, AND STRAUB [2003]

Gefen, Karahanna, and Straub [2003] examined the concepts of Trust and the Technology Acceptance Model in an e-commerce context. The application of TAM to e-commerce is the confirmatory aspect of this study; extending TAM to include Trust within this context is exploratory. Figure 3 illustrates the original research model posed by Gefen et al. [2003]. To evaluate the usefulness of TETRAD, we re-analyzed their models using the Purify and MIMBuild algorithms based on the reported measurement and structural models.
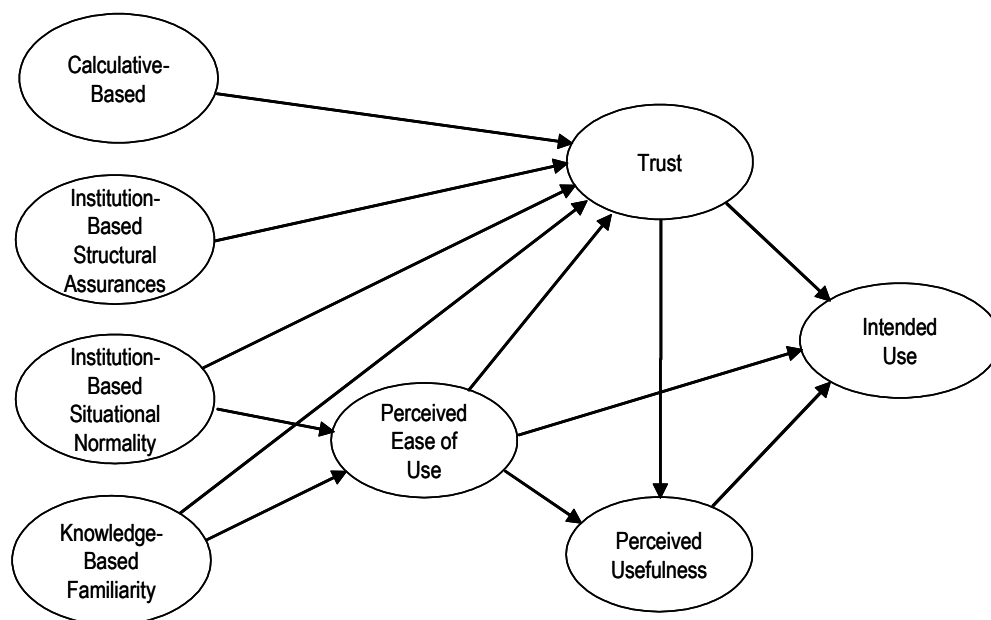

Figure 3. Gefen, Karahanna, and Straub's Structural Model on Trust and TAM

Measurement Model

We used Purify to generate pure (i.e., unidimensional) sub-models from the initial measurement model reported in the article. We constructed the same initial measurement model as the authors using the */graph* command in TETRAD. We then varied the significance level (0.05, 0.10, 0.20, or 0.30). Comparing the results across degrees of significance allows the researcher to perform a sensitivity analysis to find the best class of models.

Next, we used LISREL for confirmatory factor analyses based on the sub-models resulting from Purify. Hu and Bentler's [1999] combinatorial rule (standardized root mean square residual [SRMR] $\leq$ .08 and comparative fit index [CFI] $\geq$ .95 or root mean square error of approximation [RMSEA] $\leq$ .06) was applied to evaluate the appropriateness of fit. Table 2 shows the fit indices of the measurement models obtained by the authors and by TETRAD. Appendix B.1 lists the measurement instruments reported in the article. Appendix B.2 displays the pruned measurement model of Gefen et al. and the model derived by TETRAD.

Table 2.   Fit Indices of Measurement Models

Measurement Model	Authors' Model		TETRAD's Model		
	Initial[a]	Final[b]	Model 1[c] (α = 0.05 or 0.10)	Model 2[d] (α = 0.20)	Model 3[e] (α = 0.30)
Df	499	247	296	271	202
χ^2	881.06	364.31	391.42	349.15	232.93
SRMR	0.054	0.041	0.042	0.042	0.041
CFI	0.98	0.97	0.99	0.99	0.99
RMSEA	0.060	0.048	0.039	0.037	0.027
AIC					
- Independence	20867.71	9950.42	11808.69	10513.11	7421.52
- Model	1073.06	505.70	555.42	509.15	380.93
- Saturated	1190.00	650.00	756.00	702.00	552.00

[a] No items are pruned.
[b] Nine items pruned by the authors (see Appendix B).
[c] Seven items pruned by TETRAD.
[d] Eight items pruned by TETRAD.
[e] Eleven items pruned by TETRAD.

Each of the measurement models exhibits an acceptable fit according to the above combinatorial rule, but the pruned items varied somewhat between the authors' method and the Purify algorithm. We cannot find any specific pattern for items dropped across the different tests in Table 2 (see Appendix B.2 for additional details). Half of the items dropped were from established scales and the remaining items were developed by the authors for this study. Some items from well-established scales, such as "Perceived Ease of Use" and "Perceived Usefulness," suffered from impurities identified both by the authors and by TETRAD.

An additional fit index called Akaike's Criterion (AIC) is introduced for comparison of non-nested models [Akaike 1974]. The results show that Model 3 may be considered the best measurement model because it has the lowest AIC model index. However, in selecting the best model, we should factor in whether the items dropped can inadvertently change the meaning of the original construct. TETRAD users should collect additional information when making decisions concerning which measures to retain or drop. Thus, the best model eventually should be determined based on theoretical implications as well as statistical results. This issue, however, is not unique to TETRAD. Similar concerns can be raised with other techniques such as PLS and LISREL.

Overall, we find that with the TETRAD approach to purify measures, a researcher is able to define unidimensional variables with confirmatory fit indices that are comparable to the measurement models defined using other construct validity methods.

Structural Model

We employed the measurement sub-models generated by TETRAD in Table 2 as the input and tested the twelve paths hypothesized by the authors using LISREL. Table 3 shows the fit indices of the structural models. First, the structural models using the TETRAD-based sub-models share the same pattern of significant paths documented by the authors. That is, the authors report 11 significant paths among the 12 hypothesized paths. The structural models by TETRAD have the same pattern of significance. Second, all models in Table 3 have satisfactory fit indices. The AICs show that the TETRAD model using Model 3 is better than other TETRAD models. However, we should again be cautious in selecting the last model with the largest number of pruned measures.

When we select the structural model based on measurement sub-models generated by TETRAD, we should take into account fit indices as well as the characteristics of structural and measurement models with respect to the theory.

Next, we generated a structural model based on the measurement Model 3 using TETRAD's MIMBuild (α = 0.05) (Figure 4). The */graph* command in the input file was used to specify the selected indicators for each latent variable. The non-directional path implies a direct path between two variables, but the direction varies. The bidirectional paths in Figure 4 indicate that two latent variables are causally connected, but that one is not an ancestor of the other and vice versa. The only possibility is that there is another latent common cause of both.

Table 3. Fit Indices of Structural Models

Input Measurement Model[a]	Author's Model	TETRAD's Model		
	Final	Model 1	Model 2	Model 3
Df	257	306	281	212
χ^2	389.77	419.28	375.39	258.88
SRMR	0.05	0.052	0.051	0.051
CFI	0.96	0.99	0.99	0.99
RMSEA	0.049	0.042	0.040	0.032
AIC				
- Independence	9950.42	11808.69	10513.11	7421.52
- Model	513.19	563.28	515.39	386.88
- Saturated	650.00	756.00	702.00	552.00

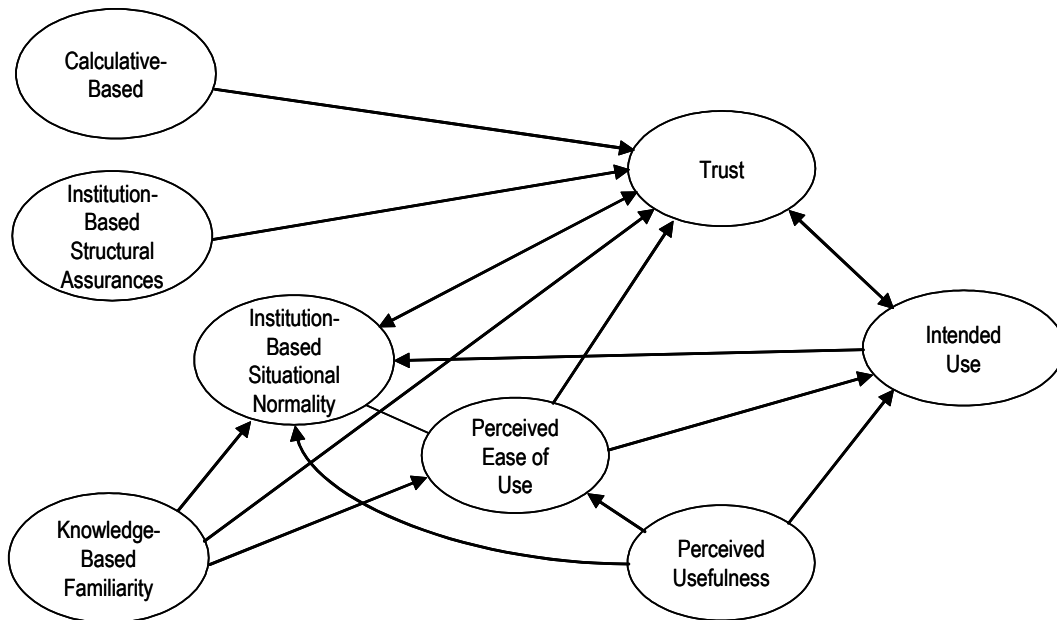[a] The measurement model identified in Table 2.

Figure 4. TETRAD's Structural Model on Trust and TAM

We compared the paths of the structural models suggested by the authors with the ones generated by TETRAD's MIMBuild (Table 4). The two paths generated by the MIMBuild module could have been reversed or eliminated after imposing temporal precedence on the structural model (e.g., "intended use" postdates other variables). However, we could not impose this temporal knowledge because this can only be added to Build, not to Purify or MIMBuild.[6]

Table 4. Structural Paths Based on Gefen, Karahanna, and Straub's Framework

Path	Authors' Model	TETRAD's Model
1. Calculative-based vs Trust	→	→
2. Institution-based structural assurances vs Trust	→	→
3. Institution-based situational normality vs Trust	→	← →
4. Institution-based situational normality vs Perceived ease of use	→	—
5. Knowledge-based familiarity vs Trust	→ (n.s.)	→
6. Knowledge-based familiarity vs Perceived ease of use	→	→
7. Knowledge-based familiarity vs Institution-based situational normality		→
8. Perceived ease of use vs Perceived usefulness	→	←
9. Perceived ease of use vs Intended Use	→	→
10. Perceived ease of use vs Trust	→	→
11. Perceived usefulness vs Institution-based situational normality		←[a]
12. Perceived usefulness vs Intended Use	→	→
13. Trust vs Perceived usefulness	→	
14. Trust vs Intended Use	→	← →
15. Intended Use vs Institution-based situational normality		←[a]

[a] This path could have been reversed or eliminated after imposing additional temporal knowledge.

Overall, the two sets of paths are mutually consistent with regard to the number of structural paths and their directions. A few differences deserve more scrutiny. In the author's model, the following antecedents of "trust" in e-commerce are exogenous variables: calculative-based trust, knowledge-based familiarity, institution-based structural assurance, and institution-based situational normality. Knowledge-based familiarity refers to familiarity with an e-vendor. Structural assurance is based on safety nets such as legal recourse, guarantees, and regulations that exist to protect online users. Situational normality conceptualizes the belief of users about the success of the transaction based on how normal or customary the situation appears to be.

In the TETRAD model, institution-based situational normality becomes an endogenous focal variable that is connected with all subsequent variables. Knowledge-based familiarity impacts

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[6] This can be considered a serious limitation of TETRAD 3. The users, however, can add background knowledge to BUILD and run the model using the correlation matrix at the structural level. The advantage of MIMBUILD is that it runs based on the measurement model. This limitation is being resolved in TETRAD 4.

institution-based situational normality (path 7 as noted in the first column of Table 4). This implies that familiarity with the vendor influences the extent to which users believe whether the interaction with the vendor is normal compared with other similar interactions. The result also suggests that users' beliefs about how normal or customary a Web site is compared with other similar ones (i.e., situational normality) may weigh more than other trust antecedents based on the simple comparison of the number of connections with other constructs (path 3, 4, 7, 11, and 15). The previous results of TETRAD can be leveraged to explore different relationships among the antecedents of trust in e-commerce and between the antecedents of trust and the remaining variables.

The TETRAD model also shows that trust is connected with situational normality and intended use through bidirectional arrows (path 3 and 14). These bidirectional arrows denote that there may be other latent common causes of trust and situational normality, and trust and intended use, respectively. The literature on trust has characterized trust as a) a set of specific beliefs that comprise integrity, benevolence, and ability of another party and b) a general belief that another party can be trusted [Gefen et al. 2003]. Researchers in the tradition of social psychology (especially the theory of reasoned action) have taken the former position and have separated trust from intended behavior. This distinction, however, is not clear when economic transactions are involved [Hosmer 1995]. The authors are aligned with the former research stream and have treated trust as a separate construct. The authors have successfully defended their position by showing that there is construct validity between the two constructs. However, the results of TETRAD raise the possibility that trust and behavioral intentions can be an integrated concept (path 14). We should keep in mind that some researchers argue that behavioral intentions are inseparable from trust and can be a proxy for trust when social relationships between the parties involve economic transactions [Gulati 1995]. Thus, TETRAD suggests an alternative way of conceptualizing trust when the research setting involves more than interpersonal interactions.

EXAMPLE 2: PAVLOU AND GEFEN [2004]

Pavlou and Gefen [2004] proposed that the perceived effectiveness of three IT-enabled institutional mechanisms (i.e., feedback mechanisms, third-party escrow services, and credit card
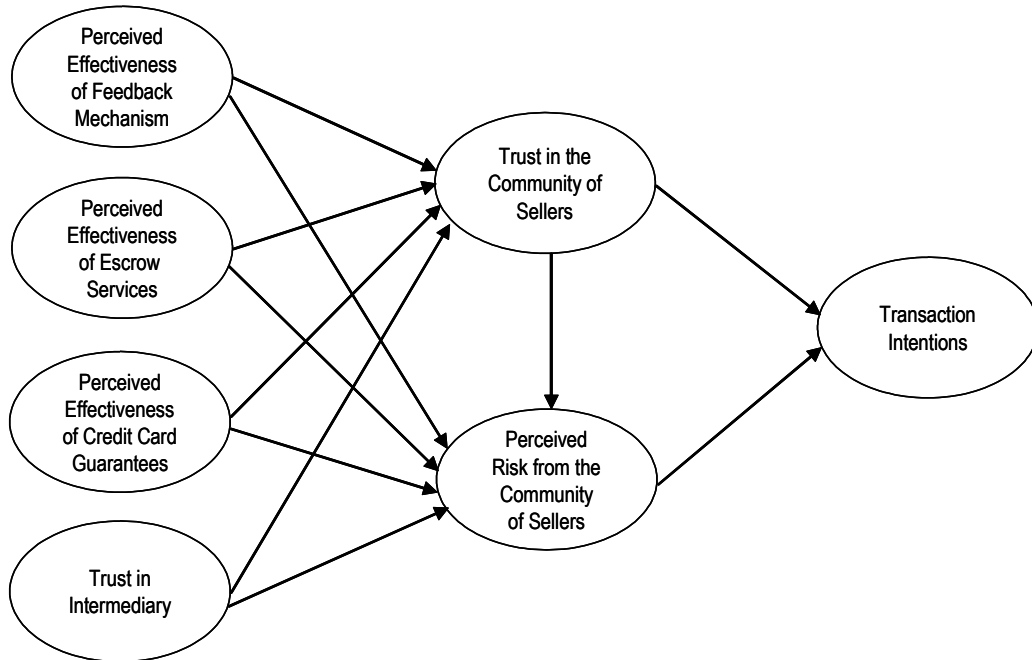

Figure 5. Pavlou and Gefen's Structural Model on Trust and IT-Enabled Institutional Mechanisms

guarantees) engender buyer trust in the community of online auction sellers. We generated a structural model using TETRAD's MIMBuild (α = 0.05) based on the author's measurement model. Figures 5 and 6 display the structural models proposed by the authors and developed by TETRAD, respectively.
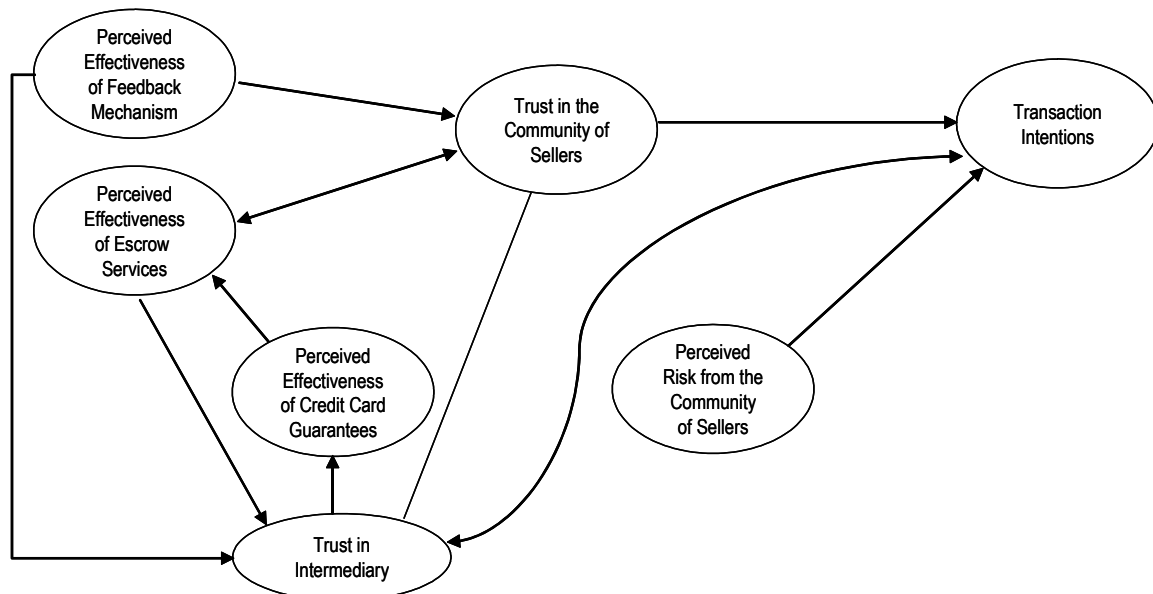

Figure 6. TETRAD's Structural Model on Trust and IT-Enabled Institutional Mechanisms

Table 5 lists the two structural models that resulted from the authors and TETRAD. We can make a few interesting observations after comparing the above models. The authors proposed their initial model (see Figure 5) and presented a revised model after dropping non-significant paths (see Table 5). The authors justified the revised model for parsimony [Pavlou and Gefen 2004: p. 49] and did not provide any details to support the model revision. The most important characteristic of the revised model is that "perceived risk from the community of sellers" is no longer associated with (i.e., insignificant) the four institutional structures (i.e., three IT-enabled institutional mechanisms and Trust in intermediary).

Interestingly, TETRAD's model in Figure 6 reflects the revised structural model by the authors in that "perceived risk from the community of sellers" is no longer influenced by the four institutional structures. This demonstrates that TETRAD can predict important theoretical relationships without relying on preliminary information about associations among the constructs. It is not clear whether the insignificance associated with "perceived risk from the community of sellers" reflects the true model, or is caused by imperfect measurement. It may be useful to measure perceived risk from the community of sellers after controlling for an individual's risk propensity. In addition, the authors' approach of measuring risk by using negative wording could have introduced another method variable in survey-based research.

Furthermore, the TETRAD model includes a few additional paths pertaining to the interrelationships among the four antecedents. Specifically, as in Example 1, the TETRAD model suggests an ordering among the antecedents of trust in the community of sellers. Among the four variables of institutional structures, two variables (i.e., perceived effectiveness of credit card guarantees and trust in intermediary) became endogenous. In addition, trust in intermediary (paths 3, 6, 10, 12, and 13 as noted in the first column of Table 5) became as important as trust in the community of sellers (path 1, 4, 10, and 15) with respect to the number of connections with other constructs. The path between perceived effectiveness of credit card guarantees and trust in the community of sellers is not significant (path 7). The authors justified this insignificance by

citing a study that described the weak effect of credit card protection on trust and perceived weak protection of financial risk by third parties. The TETRAD model also reports insignificance.

Table 5. Structural Paths Based on Pavlou and Gefen's Framework

Path	Authors' Model	TETRAD's Model
1. Perceived Effectiveness of Feedback Mechanism vs. Trust in the Community of Sellers	→	→
2. Perceived Effectiveness of Feedback Mechanism vs. Perceived Risk from the Community of Sellers	→ (n.s.)	
3. Perceived Effectiveness of Feedback Mechanism vs. Trust in Intermediary		→
4. Perceived Effectiveness of Escrow Services vs. Trust in the Community of Sellers	→	← →
5. Perceived Effectiveness of Escrow Services vs. Perceived Risk from the Community of Sellers	→ (n.s.)	
6. Perceived Effectiveness of Escrow Services vs. Trust in Intermediary		→
7. Perceived Effectiveness of Credit Card Guarantees vs. Trust in the Community of Sellers	→ (n.s.)	
8. Perceived Effectiveness of Credit Card Guarantees vs. Perceived Effectiveness of Escrow Services		→
9. Perceived Effectiveness of Credit Card Guarantees vs. Perceived Risk from the Community of Sellers	→ (n.s.)	
10. Trust in Intermediary vs. Trust in the Community of Sellers	→	—
11. Trust in Intermediary vs. Perceived Risk from the Community of Sellers	→ (n.s.)	
12. Trust in Intermediary vs. Perceived Effectiveness of Credit Card Guarantees		→
13. Trust in Intermediary vs. Transaction Intentions		← →
14. Trust in the Community of Sellers vs. Perceived Risk from the Community of Sellers	→	
15. Trust in the Community of Sellers vs. Transaction Intentions	→	→
16. Perceived Risk from the Community of Sellers vs. Transaction Intentions	→	→

As observed in example 1, the trust variables are associated with other variables in bidirectional arrows (i.e., trust in intermediary and transaction intentions - path 13, and trust in community of sellers and perceived effectiveness of escrow services - path 4). These bidirectional arrows signify the existence of other latent common causes between the variables. During the early stage of theory development, researchers may make use of the above findings to examine whether it is appropriate to separate trust from other associated behavioral intentions.

SUMMARY OF FINDINGS

The two examples show that the TETRAD results largely confirm the models provided by the authors. In example 2, TETRAD was not quite as accurate in matching the authors' refined

model. However, it did generate an accurate pattern associated with "perceived risk from the community of sellers" – the key characteristic of the revised model. Overall, this demonstrates that the data-driven approach can be as insightful as the models developed through rigorous theory-based mental experiments.

In example 1, the measurement models by the authors and by TETRAD are indistinguishable with regard to the fit indices. This implies TETRAD is effective in purifying the initial measurement. The results from the structural models via TETRAD suggest that the antecedents of e-commerce trust can be put in order. In example 1, we found that institution-based situational normality may be affected by other antecedents and may be the focal variable among independent variables. In example 2, the results suggest that the institutional structures may have an order to them and do not have uniform effects on trust. In examples 1 and 2, TETRAD suggests that trust and associated behavioral intentions may be conceptualized in an integrated manner.

In examples 1 and 2, TETRAD shows reverse causality of the temporal precedence of attitude over intended behavior. This occurred because MIMBUILD in version 3 cannot accommodate background knowledge. This observation, however, gives us an important indication regarding data collection. In non-experimental research, it is always possible to create a reordering of constructs in the data while the theoretical constructs have a temporal order to them. The best way to ward off this concern is to secure data collection processes so that the order is preserved. Otherwise, researchers should be able to theoretically and statistically refute the possibility of reverse causality when that concern is raised [Rothaermel and Deeds 2004]. In these examples, TETRAD can help us to identify this possibility during the early stages and this information can be subsequently used to preserve the intended order of constructs.

However accurate TETRAD's results are, and considering the potential theoretical relationships researchers already have in mind, TETRAD's results only provide a starting point. Our interpretations above are ex post theoretical plausibility for the generated models. As outlined in the next section, researchers should make more effort to collect additional information in order to select the right model.

IV. DISCUSSION

The results from the above examples demonstrate that TETRAD is a useful tool for uncovering potential theoretical relationships, especially when prior knowledge of underlying theory bases is lacking. Since most IS studies involve some degree of exploration, IS researchers may find the method necessary for their research. Moreover, they may find it useful if they properly apply it in the early stage of their research.

During the early stage, researchers can apply TETRAD in combination with traditional techniques such as PLS, LISREL, or EQS. If the sample size is big enough, researchers can split the samples, and use TETRAD for one half and employ traditional techniques for the other half. This approach enables the researchers to triangulate their potential models from two different angles, but one angle is not necessary to vouch for the other.[7]

While TETRAD allows rich data analyses, researchers should not capitalize on chance when building causal models and interpreting results [Ting 1998]. TETRAD allows researchers to enter background knowledge into the TETRAD program prior to the search for causal models, so that the knowledge constrains the TETRAD program to discover the causal models that make theoretical sense. If model searching becomes fishing, then parameter estimation will also be fishing. The TETRAD-based approach can be seen as collaboration between human reasoning and computer automation.

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[7] We appreciate the associate editor for this insight.

Theoretical sources and prior knowledge are by no means ignored. The process of model specification in social science research can be regarded as a search and decision making process. Researchers search a class of models, assess various models, and then make a choice among the alternatives [Scheines et al. 1998b]. This process is often performed as a mental exercise. Because of the complexity of social phenomena, the search space is large, and there are often theoretically plausible alternatives to a given model. These alternatives can provide entirely different causal conclusions. Facing such an ill-defined and complex situation, human beings are required to have unlimited cognitive capabilities (full rationality) to derive the optimized results. However, cognitive psychology asserts that humans only have "bounded rationality" [Simon 1986; Simon 1996]. With limited time and limited cognitive capability, researchers find the job of choosing the most plausible model challenging, if not impossible. Under such situations, computer-aided tools can be very helpful.

The TETRAD-based method does not imply that theoretical sources will be replaced with automatic procedures to specify models. Existing theories and available domain knowledge are employed to justify the constraints of model specification. In social science research, however, theories and prior knowledge can rarely be sufficiently confirmed and sufficiently strong to entail a unique model specification [Scheines et al. 1998b]. Therefore computer-aided tools such as TETRAD are still needed in the search and decision making process of model specification. Indeed, recent developments in computer science and cognitive psychology have led to broader acceptance of computer-aided knowledge discovery methods and their use in advancing scientific knowledge in many areas [Fayyad et al. 1996; Langley 2000]

Researchers are usually not sensitive to equivalent or alternative models. The existence of equivalent or alternative models that fit the data equally well but have quite distinct causal relationships would make a theory quite vulnerable to the possibility of falsification. But then on what basis should we prefer one of the models generated by TETRAD over another? The data themselves will not help choose the right model because the models are all consistent with the data. We must provide additional information to make the choice. We can refine existing constructs or variables, add more variables, conduct laboratory experiments, or collect data using different methods for triangulation [Scheines et al. 1998b]. When sufficient additional information is added, the interpretation of the model will not be ambiguous and the model quality will be determined by its substantive meaningfulness [Maccallum et al. 1993]. Thus, after using TETRAD to discover causal models consistent with the data, researchers should make further efforts to make their models robust [Ting 1998].

The TETRAD approach is not without limitations. First, TETRAD currently performs conditional independence tests through vanishing partial correlations when data conform to multinomial distributions. However, it is not known how to perform conditional independence tests when the distributional assumption is not met, and how reliable partial correlation tests are at detecting conditional independence when multivariate normality is not met [Scheines et al. 1998a]. Second, background knowledge can be added only to Build, not to Purify or MIMBuild. In Purify, the user cannot specify correlated errors that happen in longitudinal designs and cannot insist on some impure indicators being included. This limitation is under improvement in the latest version, TETRAD 4. Third, TETRAD generates latent variables with certain combinations of indicators based on statistical signatures of certain configurations, and does not provide any interpretation for them. If they do not confirm what we already know, then we must reinterpret those with additional evidence and justification. Last, TETRAD cannot incorporate moderators into the model. Researchers need to rely on other statistical tools for insights on moderation.

V. CONCLUSION

Information Systems research has been criticized for a lack of theoretical maturity and methodological rigor. In order to advance the field, it is critically important to employ appropriate statistical methods that can facilitate theory development. In this paper, we introduced the origins, philosophies, algorithms, and modules of TETRAD. We also illustrated how TETRAD can be

used for additional insights after re-analyzing the correlation-based measurement and structural models reported in two published IS articles. The results showed that TETRAD can generate measurement and structural models that are largely consistent with those reported in the articles, and can also produce alternative models worth further exploration. We encourage IS researchers to employ this tool at the early stages of theory development to have better and rich insights of their models.

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APPENDIX A: SEARCH ALGORITHMS IN TETRAD 3

This paper relies on TETRAD version 3 to describe the search algorithms. Version 3 does not include statistical functions necessary for parameter estimation. Therefore, once a set of models is generated, these models should be examined in another statistical package, such as LISREL or EQS, for estimation and testing.[8] In TETRAD 3, Build, Purify, and MIMBuild are the major algorithms (modules) used to search for recursive models consistent with the background knowledge used to constrain the covariance matrix [Scheines et al. 1997; Scheines et al. 1998b]. TETRAD requires input matrix and alpha or Type 1 error probability. Users can make "causal sufficiency" assumption in deriving the result, meaning the causal structure of the constructs is

[8] Version 4 is under development and provides more search algorithms along with an easy to use graphical user interface. Additionally, version 4 includes statistical functions for parameter estimation.

explained purely by relationships among the constructs without additional latent or unobserved constructs [Spirtes 2001].

Build represents the partial correlation equivalence class of structural models consistent with the background knowledge from sample data [Scheines et al. 1997]. The background knowledge may include the existence of correlated errors or latent common causes, time ordering among the constructs, known causal relationships among the constructs, and causal relationships among the constructs known not to exist. The Build module finds structural models by performing statistical tests to examine vanishing (partial) correlations among the variables. This module has the most representational flexibility over others in TETRAD 3. It tests direct causal relations between indicators, linkages between latent constructs, and linkages among indicators across latent constructs. The Build module can be useful for determining whether a latent variable for the selected indicators exists, whether a boundary of a latent construct is definite or can be extended to include additional indicators, or whether causal relations exist between indicators. Researchers can make use of the previous features to establish content validity of a structural model.

Purify generates a pure sub-model of the initial measurement model based on a list of latent constructs and the associated measurement model. A measurement model is pure (i.e., unidimensional) if each indicator is reflective, is a direct effect of exactly one latent construct, and has uncorrelated error terms. Establishing a unidimensional measurement model is important because the correlations among the latent constructs may be estimated consistently under the condition of unidimensionality. Thus, the plausible structural models can be uncovered more easily. First, researchers need to incorporate background knowledge to build a measurement model for each latent construct. Then, the researcher should employ the Purify algorithm to search for a sub-model of the original specified measurement model. Vanishing tetrads are used for the search processes. Given the multiple sets of indicators, Purify can generate multiple alternative unidimensional measurement models. The reliability of Purify depends on the significance level and sample size. Purify prunes more items as the significance level increases and fewer items as the significance level decreases.[9] This module is useful to establish the construct validity of a measurement model, particularly in an exploratory context.

MIMBuild (Multiple Indicator Model Builder) generates a set of recursive structural models with latent variables that share a common pure measurement model. It assumes that the data are multivariate normal, and the measurement model is pure. Using the tests of vanishing tetrad differences, MIMBuild constructs a set of structural models that entail vanishing partial correlations among latent variables judged to hold in the population. The syntactic requirements of Purify and MIMBuild are that each latent variable has at least two indicators, and each indicator measures a latent variable and is not formative. In generating structural models, MIMBuild requires measurement models whereas Build does not demand such models.

APPENDIX B: MEASUREMENT MODELS BASED ON GEFEN, KARAHANNA, AND STRAUB [2003]

APPENDIX B.1: MEASUREMENT INSTRUMENTS

Latent variable	Item	Wording
Intended Use	USE1	I would use my credit card to purchase from the online vendor.

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[9] An item can be considered impure if it does not vanish in the population when it is supposed to vanish in a tetrad difference (τ), and thus becomes a target for pruning. Given the significance level α, a tetrad difference is considered to be equal to zero if $P(\tau) \geq \alpha$ [Scheines et al. 1997]. In this case, the higher the significance level, the more difficult a tetrad difference is judged to vanish.

	USE2	I am very likely to provide the online vendor with the information it needs to better serve my needs.
Perceived Ease of Use	EOU1	The Web site is easy to use.
	EOU2	It is easy to become skillful at using the Web site.
	EOU3	Learning to operate the Web site is easy.
	EOU4	The Web site is flexible to interact with.
	EOU5	My interaction with the Web site is clear and understandable.
	EOU6	It is easy to interact with the Web site.
Perceived Usefulness	PU1	The Web site is useful for searching and buying CDs/books.
	PU2	The Web site improves my performance in CD/book searching and buying.
	PU3	The Web site enables me to search and buy CDs/books faster.
	PU4	The Web site enhances my effectiveness in CD/book searching and buying.
	PU5	The Web site makes it easier to search for and purchase CDs/books.
	PU6	The Web site increases my productivity in searching and purchasing CDs/books.
Trust	KB1	Based on my experience with the online vendor in the past, I know it is honest.
	KB2	Based on my experience with the online vendor in the past, I know it cares about customers.
	KB3	Based on my experience with the online vendor in the past, I know it is not opportunistic.
	KB4	Based on my experience with the online vendor in the past, I know it provides good service.
	KB5	Based on my experience with the online vendor in the past, I know it is predictable.
	KB6	Based on my experience with the online vendor in the past, I know it is trustworthy.
	KB7	Based on my experience with the online vendor in the past, I know it knows its market.
Calculative-Based	CB1	The online vendor has nothing to gain by being dishonest in its interactions with me.
	CB2	The online vendor has nothing to gain by not caring about me.
	CB3	The online vendor has nothing to gain by not being knowledgeable when helping me.
Familiarity with the E-Vendor	FV1	I am familiar with the online vendor through reading magazines/newspaper articles or ads.
	FV2	I am familiar with the online vendor through visiting the site and searching for CDs/books.
	FV3	I am familiar with the online vendor through purchasing CDs/books at this site.
Structural Assurances	IB1	I feel safe conducting business with the online vendor because the Better Business Bureau will protect me.
	IB2	I feel safe conducting business with the online vendor because of it provides a 1-800 number.
	IB3	I feel safe conducting business with the online vendor because of its statements of

		guarantees.	
	IB4	I feel safe conducting business with the online vendor because I accessed its site through a well-known, reputable portal.	
Situational Normality	SN1	The steps required to search for and order a CD/book are typical of other similar Web sites.	
	SN2	The information requested of me at this Web site is the type of information most similar type Web sites request.	
	SN3	The nature of the interaction with the Web site is typical of other similar type Web sites.	

APPENDIX B.2: REFINED MEASUREMENT MODELS

Latent Variable	Item	Dropped by Gefen et al.	Dropped by TETRAD at 0.05/0.10	Dropped by TETRAD at 0.20	Dropped by TETRAD at 0.30
Intended Use	USE1				
	USE2				
Perceived Ease of Use	EOU1	Yes			
	EOU2		Yes	Yes	Yes
	EOU3				Yes
	EOU4				
	EOU5		Yes	Yes	Yes
	EOU6	Yes			
Perceived Usefulness	PU1	Yes	Yes	Yes	Yes
	PU2				
	PU3			Yes	Yes
	PU4				Yes
	PU5	Yes	Yes	Yes	Yes
	PU6				
Trust	KB1				
	KB2		Yes	Yes	Yes
	KB3		Yes	Yes	Yes
	KB4	Yes			Yes
	KB5				
	KB6	Yes			
	KB7				
Calculative-Based	CB1				
	CB2				
	CB3				

Familiarity with the E-Vendor	FV1	Yes			
	FV2				
	FV3				
Structural Assurances	IB1				
	IB2				
	IB3				
	IB4	Yes	Yes	Yes	Yes
Situational Normality	SN1				
	SN2				
	SN3	Yes			

ABOUT THE AUTHORS

Ghiyoung Im is an assistant professor in the Decision Sciences Department at Clark Atlanta University. His interests center on organizational learning and knowledge management enabled by information technology, and their implications for firm strategy, the competitiveness of nations, and solutions to social problems. His current research interests are in knowledge transfer in interorganizational relationships. His research has been published in *The DATA BASE for Advances in Information Systems*, *Expert Systems with Applications*, and *Information Systems Journal*. He received his Ph.D. from Georgia State University and an M.S. from NYU Stern School of Business.

Jijie Wang is a Ph.D. candidate in the Department of Computer Information Systems at Georgia State University. She received her Bachelor's degree in Accounting from Beijing University, P. R. China, and Master's degree in CIS from Georgia State University. Her work has been presented at *Americas Conference on Information Systems* and *Information Resources Management Association International Conference*, published in *Encyclopedia of E-Commerce, E-Government, and Mobile Commerce*, and *Human-Computer Interaction and Management Information Systems: Applications*, and accepted at *Information Resource Management Journal* and *Decision Sciences*. Her dissertation focuses on the use and management of mobile computing technologies in organizations, and her other research interests include IT project management, open source software community, and research methodology in information systems research.