Abstract

The lack of theories and methodological weakness have been pointed out as two distinct but related problems in empirical management information systems (MIS) research. Reinforcing the existing belief that too much attention has been devoted to "what" as opposed to "why" or "when" relationships exist, this paper focuses on a subset of modeling and methodology issues involving the systematic discovery and representation of causal relationships. Our analysis of the existing empirical MIS literature reveals the need to build richer causal models, to increase the flexibility of model representation, to integrate the isolated worlds of pure latent and pure manifested variables, and to provide a tighter linkage between the exploratory and confirmatory research phases.

Based on philosophy of science and advances in the fields of experimental economics and sociology, we propose a foundation for developing richer models by explicitly considering the exogeneity and endogeneity of constructs and a manipulative account of causality, and by recognizing the role of incentives, agent, and organizational characteristics in MIS models. Since richer models require more flexible tools and techniques, the paper describes the representational shortcomings and statistical pitfalls of factor-analytic methods commonly deployed in empirical research. We suggest that weak exploratory phase tools and approaches may allow violations of causal assumptions to pass undetected to the confirmatory phase. Since confirmatory tools like LISREL also make factor-analytic assumptions, these violations are not likely to be detected at the confirmatory phase either. We propose using TETRAD, a non-parametric tool, at the exploratory phase for its ability to accommodate a wide variety of causal models. The findings are summarized within an integrated framework, which enhances the likelihood of discovering relationships through richer theoretical support and powerful exploratory analysis.
Keywords: MIS research methodology, causality, exogeneity, endogeneity, manipulative account, LISREL, TETRAD

ISRL Categories: AI01, AI04, AI06, AI07, AI08, DA, HD

Introduction

Management information systems (MIS) research shares all the difficulties and challenges associated with the social sciences. As a business discipline, MIS research should be directed toward helping managers improve business processes and competitiveness through the deployment of information technology (IT). Rapid changes in IT and organizational structure are necessitating a deeper understanding of how IT can impact organizational performance. This objective calls for studies focusing on the theory-based discovery of causal relationships between IT, organizational and economic factors. Both the academic community and business organizations can benefit from parallel improvements in theory development and data analysis techniques which can lead to such discoveries.

The state-of-the-art practices in MIS field research are analyzed and ways to improve model development as well as exploratory phase analysis techniques are investigated. In concurrence with Cooper's (1988) position, we conclude from a survey of research articles appearing in several major U.S. MIS journals during 1989-1995 that the primary focus of field research in MIS has been on "what" relationships exist as opposed to "why" or "when" relationships exist. As an example, consider a paradox emerging in the reengineering literature. While the reengineering doctrine of "radical change" (Hammer and Champy 1993) is intuitively appealing, and while there are documented cases of success through drastic change measures, a small but growing literature shows a paucity of systematic evidence regarding the relationship between radical change and reengineering success (Barua, et al. 1996). In the absence of explicit modeling and theoretical justification of why and when radical change leads to success, a simplistic model of reengineering payoff through radical change can provide misleading results. Incorporating "why" or "when" aspects of a relationship in a model results in an enriched and more accurate representation of the problem of interest. Along these lines, one key objective of this paper is to develop guidelines for building rich models.

A rich model requires flexible tools and analysis techniques which enable rather than constrain the researcher from representing and analyzing the model in both exploratory and confirmatory research phases in accordance with his/her theory. We find that existing tools such as exploratory factor analysis are both conceptually and statistically inadequate for this purpose and that incorrect modeling assumptions and measurement problems can carry over to the confirmatory phase without being detected. The state-of-the-art in confirmatory research in MIS is based on Bagozzi's (1977; 1979; 1981; 1982a; 1982b) and Churchill's (1979) frameworks for measurement and analysis, which have been implemented in the form of LISREL. A small fraction of the MIS community has adopted the Bagozzi-Churchill framework for measurement and validation, and LISREL as the primary confirmatory tool (e.g., Cooprier 1990; Sethi and King 1991; Straub 1989; Taylor and Todd 1994; Venkatraman 1989; Zaheer and Venkatraman 1994) for confirmatory research. While this is a useful step toward improving confirmatory research in MIS, its limitations include restrictive model representation and untested statistical assumptions.

Interestingly, there appears to be a conflict between two schools of thought regarding exploratory and confirmatory MIS research. One prescription for the lack of theory in MIS has been to admit that we do not have established theories to be deployed in confirmatory research and to concentrate on the exploratory phase instead (Kauber 1986; Klein and Lyytinen, 1985). Others, however, call for increased methodological rigor in confirmatory research involving instrument validity and reliability. While many researchers recommend
closer ties with reference disciplines for compensating the lack of theories in MIS, others suggest breaking this "umbilical cord." We believe that these two sets of concerns (more emphasis on exploratory research and more rigorous confirmatory research) are an integrated problem, necessitating improvements in both conceptual theory building and empirical approaches to representing and analyzing causal relationships.

While research methodology is a wide field of research by itself, the focus here is on the systematic discovery of causal relationships based on theory development, improved model representation and analysis techniques which integrate both exploratory and confirmatory phases. We suggest three critical steps in this discovery process. First, we call for a richer theoretical foundation for developing causal models, which will provide a better justification of "why" and "when" relationships exist rather than "what" relationships exist (Cooper 1988). This a priori justification will increase the likelihood of discovering valid relationships, similar to the exploration for natural resources only in those areas where the researcher has strong a priori theoretical reasons to believe that the region is likely to be rich in such resources. Based on philosophy of science, the seminal work in economics (Marschak 1950; Simon 1953) and in sociology (Holland 1986; Sobel 1995), and some key developments in experimental economics (Smith 1982, 1989), we propose a conceptual foundation for model building through a better justification of endogenous and exogenous variables (or constructs), a manipulative account of causal relationships, and explicit testable assumptions about "agent" behavior based on characteristics of incentives and reward systems, IT, organizational and business processes.

Second, before the discovery takes place, the problem of interest is expressed as a model with certain assumptions regarding the researcher's beliefs about the real world. We suggest that strong assumptions and modeling restrictions, which may not follow from a conceptual or theoretical standpoint, but which may be required by a particular tool or empirical approach, reduce the likelihood of success in the discovery process. Such requirements may force a researcher to represent a model in a way which is different from what would be suggested by theory; further, convenient modeling assumptions, which again may not be supported by theory, can draw the researcher's attention away from additional relationships critical to the enrichment of the overall model. Third, we believe that it is wrong to assume that our initial theories, however rich they may be, are infallible; when data do not support a posited theory, and when there is reason to believe that the quality of data is high, the falsified theory has to be enhanced and/or modified.

We propose using TETRAD (Glymour et al. 1987) at the exploratory stage as an alternative tool to parametric approaches such as exploratory factor analysis. We suggest that the flexibility of model representation, the lack of untested statistical assumptions, and the ability to detect missing variables and links make TETRAD a strong candidate for a tool that can help mitigate some major pitfalls of factor-analytic approaches. In conjunction with the guidelines we propose, TETRAD should help facilitate the development of new theories through the systematic discovery of causal relationships and build a bridge from the exploratory to the confirmatory research stages.

Causal Modeling

Causal modeling has always been a controversial issue in empirical research. Notions of causality have evolved from deterministic to probabilistic and statistical accounts (for excellent summaries, see Skyrms (1988) and Sobel (1995)). The ontological aspect of causality involves the characterization of the relationship between a cause and its effect(s). Three elements in the relation of cause and effect have been identified: temporal precedence, contiguity in time and space, and constant conjunction (Hume 1977). Constant conjunction implies that it must be possible to repeat the effect of a cause every time the appropri-
The opponents of the Humean school of thought are called "realists" or "natural necessity theorists." They focus on mechanisms or processes connecting cause and effect (i.e., the "why" and "when" aspects), while regularity theorists emphasize scientific laws or universal generalization (Bagozzi 1980). Thus, the realists advocate a stimulus-organism (mechanism)-response (S-O-R) model, while the Humean school studies phenomena as S-R models (Bagozzi 1980). Shortly we argue that empirical research in MIS has primarily followed the regularity theorist's view and discuss the implications thereof.

Hume's focus on temporal precedence has been subject to much criticism (e.g., Collingwood 1948; Sobel 1995) on grounds of not recognizing the possibility of contemporaneous causation and events that may take place between the occurrences of a cause and its effect. In fact, Simon (1953) explicitly and purposely avoids the temporal aspect of Humean causality in his study of causal modeling:

By putting asymmetry (between two variables A and B), without necessarily implying a time sequence, at the basis of our definition we shall admit causal orderings where no time sequence appears (and sometimes exclude them even where there is a time sequence). By so doing we shall find ourselves in closer accord with actual usage . . . . We shall discover that causation (as we shall define it) does not imply time sequence, nor does time sequence imply causation.

The prevailing concept of causality in social sciences does not consider time explicitly either.

If A causes B then some changes in A must be accompanied by changes in B, if other variables are held constant; . . . if B changes, then A must have changed if the other variables of which B is a function did not change. So we say that if A is a cause of B, then, ceteris paribus, a change in B must be accompanied by a change in A. Or, put another way, if A causes B, then, ceteris paribus, if a change in A had not occurred, a change in B would not have occurred. (Glymour, et al. 1987)

The challenge is to operationalize the central ideas in the definition in statistical terms so that they can be applied in empirical research. In a later section, TETRAD (Glymour, et al. 1987), which uses a directed graph of a proposed causal model to determine its statistical properties, is discussed.

**Causal priority, endogeneity and exogeneity in causal modeling**

One major problem with nearly all accounts of causation (including Hume's) is causal priority (Bunge 1979; Mackie 1974; Sobel 1995). Causal priority or causal order is the key to the asymmetric nature of the relationship between a cause and its effect and is conceptually different from Hume's temporal priority. Sobel suggests that a "manipulative account" of causality can address the causal priority problem. The manipulative account requires a researcher to "manipulate an independent variable and see how the value of a response variable Y depends upon the value of the manipulated variable" (Sobel, 1995). As the proposed variable is manipulated prior to measurement of the effect, the causal priority issue is resolved. Since a researcher can truly manipulate the levels of treatment (independent) variable(s) only in an experimental setting, does it imply that causal priority can be established only in an experiment? Sobel suggests that in non-experimental settings, a researcher can still ask whether it is possible, at least in principle, to manipulate the variable(s) which the researcher would like to designate as a cause. As an example, consider incentives and performance in software development. A manipulative account would suggest that by changing the incentive (e.g., compensating by lines of code versus function points), the behavior of the developer (e.g., writing more lines of
Causal Relationships

code or function points) can be changed. Even though we are not actually manipulating the incentive in a field study, the researcher can argue that it is theoretically possible to do so. On the other hand, it is clear that we cannot even hypothetically assign values of programmer output and then observe whether the incentive changes. Thus, the causal priority becomes evident without an explicit consideration of temporal precedence.

Along related lines, the noted economist Marschak pointed out the importance of identifying and using "exogenous" variables (ones that are not determined by other variables in the model) rather than "endogenous" variables as predictors in causal relationships:

These remarks are of some importance in view of many attempts to use endogenous variables as predictors; e.g., to predict national income from contemporaneous imports, or retail sales, etc. To choose between various national policies, it cannot be useful to be able to predict national income from imports, since the latter are themselves affected by any policy chosen. (Marschak 1950)

Further, to use endogenous and exogenous variables correctly, Marschak emphasizes the need to model phenomena of interest (e.g., demand and supply in economics) as systems of equations instead of a single relationship, which is commonly encountered in empirical research in MIS. He noted a serious flaw in empirical economic studies conducted up to the late 1940s:

[Simultaneous equations] have often been forgotten by economic statisticians who tried to estimate a single stochastic relation as if no other such relations had taken part in determining the observed values of the variables. (Marschak 1950)

In a similar vein, the basic premise with which Simon (1953) initiates his pioneering research on causality is a system of equations, which implies a multiplicity of dependent variables. What is so important about describing the implications of a theory through multiple relationships? The answer lies in the exogeneity and endogeneity of the variables or constructs.

In determining the predictors of a dependent variable, the researcher must ask whether the predictors themselves are exogenous. It is quite likely that the predictors themselves depend on other variables, in which case an additional set of relationships must be formulated along with the main relationship.

For example, to assess the impact of IT on productivity, Loveman (1994) develops a model under the assumption that there is a relationship between output quantity produced by a firm and input expenditures including IT investments. A change of input levels results in a change of output quantities, and the assumption is that the inputs are exogenous. By contrast, the Barua and Lee (1997) IT productivity model assumes that firms change the levels of inputs depending on the input prices. Thus, as the price of computing falls, firms use more IT. The Barua and Lee model is a system of $n + 1$ relationships, one for the input-output linkage, and $n$ relationships describing how the firms choose $n$ inputs depending on input prices and other factors.

A similar position is taken by Sobel (1995) in sociology, who points out that a (hypothetical) study of the impact of education level ($L$) on earnings ($I$) using a single relationship between $L$ and $I$ is theoretically flawed. He suggests that the behavior of individuals in choosing their education level must be considered along with the proposed relationship between $L$ and $I$. Since the data is gathered from the field, the researcher cannot assign $L$ randomly to respondents as in an experimental setting, and must therefore consider in the model (through additional relationships) the fact that the respondents got a chance to decide their education levels.

As another example where a system of relationships would be appropriate for addressing the key aspects of a problem, consider the relationship between radical change and reengineering success mentioned in the introduction. From a theoretical standpoint, Barua et al. (1996) show that under "unfavorable" pre-existing conditions pertaining to organizational and IT characteristics, incremental rather than radical changes in the "right"
directions can lead to higher net organizational payoff. It implies that two sets of relationships may be at work here: The benefits (e.g., response time reduction, quality of transactions, etc.) may increase with changes of larger magnitude, while the cost of a given level of change increases with the unfavorable nature of pre-existing organizational and technological factors. Since financial success depends on both benefits (the revenue side) and costs, it is unlikely for a single relationship between the magnitude of change and reengineering success to be able to capture the essence of the problem. Again, the emphasis of this richer theoretical perspective is on why and under what circumstances there may be a relationship between two or more variables.

Latent and manifested variables modeling

An important aspect of an empirical model involves the latent and/or manifested nature of its variables. Latent variables are unobservable, and assumed to manifest themselves through indicator variables, while manifested variables are measured directly. Behavioral sciences primarily focus on latent variables, while econometricians and statisticians only use manifested variables (Wold 1985). One problem with the pure latent variables approach arises from its modeling assumptions. Since it is assumed that the indicator variables are caused by a latent variable, one cannot claim to change the level of a latent variable by manipulating its indicators (Holland 1986). That is, if we want our model to actually help managers in making changes (improvements), then the independent variables should be manifested in nature. Of course, if we adopt the viewpoint that many latent variables may be a conglomeration (i.e., an effect) of their indicators (even though it violates a factor-analytic assumption regarding the direction of causality), then we do not encounter this problem. It is important to note that, in the natural sciences, many breakthroughs have been achieved by introducing latent variables to explain irregularity in relationships. For example, gravitational force, electromagnetic fields, and many other variables were treated as latent when they were initially introduced (Glymour, et al. 1987).

Pure manifested modeling also suffers from the critical limitation of not being able to capture the richness of a problem. Given the multifaceted nature of the MIS field, which spans a wide range of domains including organizational behavior, psychology, economics and computer science, a purely manifested variables model will not be able to fully address the essence of the problem at hand. Hence, we take the position that we should use both latent and manifested variables based on the nature of the phenomenon being investigated. However, as described later in the analysis of the survey, we find a deep chasm between the two worlds of modeling.

Review of the Current Status of Empirical MIS Research

Apart from the issues of modeling richness and representational accuracy raised earlier, MIS studies have been criticized in the literature for less rigorous implementation of research methodologies than their reference disciplines. The criticisms include low statistical power, inappropriate research design and choice of methodologies, and inadequate instrument validation (Baroudi and Orlikowski 1989; Cooper 1988; Culnan 1986; Farhoomand 1987; Huber 1983; Jarvenpaa et al. 1985; Sethi and King 1991; Straub 1989; Vitalari 1985). To examine the current status of field research in MIS from a causal modeling standpoint, a survey of several major U.S. journals in MIS (Information System Research, MIS Quarterly, Management Science, Decision Sciences, Decision Support Systems and Organization Science) from 1989 to 1995 was conducted. For MIS Quarterly and Decision Sciences, only articles appearing in the "Theory and Research" and "Concepts, Theory, and Techniques" respectively are considered. Only MIS articles are selected from
multidisciplinary journals such as Management Science, Decision Sciences and Organization Science based on titles, abstracts and authors' affiliations.

The studies are classified according to research method (e.g., case study, experimentation, field study, etc.) as shown in Table 1. Articles using multiple research methods are classified according to the method most central to their research. Studies focusing solely on research methodology and technical issues are included in the non-empirical category, which also contains frameworks and other conceptual studies. Since most of the articles in Decision Support Systems involve purely technical rather than empirical issues, it was considered appropriate to report statistics both with and without the purely technical papers in all journals. Excluding such technical studies, Table 1 shows that empirical studies made up 52% ((24 + 46 + 90)/307) of all research during 1989-1995. Further, field research made up 56% (90/160) of the empirical studies.

Of the field research studies, 69% (62/90) proposed causal models (i.e., developed testable hypothesis linking a cause and its effect). "Survey" and "instrument development" research is classified under "field studies" but under non-causal modeling. Field studies reporting opinion surveys and organizational practice without any testable hypotheses are also classified as non-causal. Further details of the classification scheme are furnished in Appendix A.

While interpretive studies based on "post-positivist" or other recommended paradigmatic shifts such as action research (Antill 1985; Sandberg 1985; Wood-Harper 1985) and phenomenological research (Boland 1985) are crucial in generating a deeper understanding of phenomena of interest, such studies were not found in the sample. This observation is consistent with earlier findings that 96.8% of publications between 1983 and 1988 were positivist in nature (Orlikowski and Baroudi 1991). Of course, if the sample had included European journals, we would expect to observe studies in the above categories. To analyze causal modeling in field studies, we focus closely on (1) model richness, (2) the nature of variables used, (3) model estimation techniques, and (4) testing for reliability and validity of constructs.

Model richness

Of the causal field studies, 68% (42/(19 + 42 + 1)) had a single dependent variable. As pointed out in the early economics literature (Marschak 1950), this single structural equation approach is indicative of a simplistic modeling effort, with the potential danger of using endogenous variables as predictors, where in fact the endogenous variables should have been modeled as dependent on another set of relationships, and where a single relationship does not capture the essence of the problem. Parsimonious models are certainly preferable from the standpoint of tractability; however, too simple a model can even be misleading, as suggested in the earlier illustrations involving software development, IT productivity, reengineering, and education level.

Yet another example of simplistic modeling involves the theme of a positive relationship between senior management involvement and MIS project success. A new perspective on this problem is obtained by considering involvement as a decision on the part of top management. Top management may decide that its involvement in a project is important because of the project's criticality to an organization's success. With this perspective, the model has one relationship between top management involvement and success and at least another relationship positing that the higher the perceived criticality of the project, the higher the involvement. This ties well with the earlier discussion of endogeneity/exogeneity, for in the new model with the additional criticality construct, top management involvement is no longer exogenous.
Incorporating MIS specific factors

A model with a single dependent variable is also indicative of low specificity toward the MIS domain. It is critical to consider how a proposed relationship is affected by characteristics of IT, incentives, organizational and business processes. Yet, it is difficult to capture these effects in a single structural relationship, as seen in the example of IT productivity models. We believe that the familiar complaint about lack of theories in MIS can be partly addressed by adopting an enhanced perspective on modeling. That is, in addition to postulating a relationship between two or more variables, we have to explicitly consider how the characteristics of agents (e.g., MIS developers, users, senior managers), organizations (e.g., team versus functional orientation, short versus long term outlook, etc.), and incentive/reward systems (e.g., salary based, group based, etc.) can impact the relationship. When one or more of these factors are considered, what previously was a simplistic S-R relationship may turn out to be a richer S-O-R specification, where the posited exogenous variables now appear as endogenous, being governed by additional relationships. Relying heavily on reference disciplines, IS research adopts models from areas such as sociology and economics, but generally does not add any unique aspects of MIS (e.g., specific IT characteristics) to enrich the models.

Which subset of factors is important will depend on the problem at hand. For example, anonymity in group decision support systems (GDSS) has been advocated by some researchers as having a positive impact on the generation of new ideas (see Valacich et al. [1992] for a review). However, the empirical evidence regarding the benefits of anonymity can be classified as inconclusive (Barua et al. 1995). Indeed, it is possible that the impact of the anonymity feature depends on the management style of the organization (e.g., authoritarian versus participative). In an authoritarian organization, the anonymity feature may be useful in stimulating fresh ideas, but in a participatory style of management, anonymity can lead to shirking and free-riding effects (Barua et al. 1995).

The incorporation of incentives is critical for the microlevel analysis with which MIS studies are generally concerned. Incentives are an integral part of MIS topics such as software development and maintenance, end-user support, organizational design, information sharing behavior, and group interactions. Consider experiments on GDSS based interactions, where subjects are generally rewarded equally for participation. Unfortunately, they do not have the incentive or motivation to put in enough effort under such an incentive system (Barua et al. 1995). It has been pointed out that "motivation has not been a primary construct investigated in GSS [group support systems] research" (Benbasat and Lim 1993). Motivation can include both monetary and social rewards; considering incentives in causal models through additional relationships will help explain how agents choose their actions, which in turn affect outcomes of interest.

Isolation between two modeling worlds

Two separate worlds of causal modeling have been witnessed: software engineering and economics research in IS focusing exclusively on manifested variables and making up 31% (19/62) of causal field studies, and behavioral and organizational studies (68%) excluding manifested variables in their causal structures. As noted earlier, both purist approaches have serious limitations, especially for the complex problems that arise in the MIS domain. For example, in order to assess the contribution of IT to business performance, we need to know investments in hardware, software and IT personnel (manifested variables), as well as how efficiently these investments were translated into systems and skills (latent variables). This approach has been used in business value assessment (Weill 1992). No other study that followed this mixed modeling technique was found. Note that Weill's study is labeled as neither pure manifested nor pure latent, which is why the total number of causal field studies for 1992 is one more than the total number of
studies in the causal representation cell. We also observed some major limitations in the analysis of empirical models. However, some of these limitations can be adequately addressed through the deployment of advanced tools such as LISREL. Since the MIS methodology literature has already alluded to these problems, only a brief description of the findings is provided.

Measurement tool

Factor analysis (two-step estimation) was the primary tool for measurement, used by 83% (35/42) of causal field studies using latent modeling. In this two-step approach, factor scores are obtained from factor analysis; the scores are then used to separately estimate the structural relationship between the factors. However, this assumption implies that the measurement is perfect and therefore ignores measurement errors. Depending on the magnitudes of these errors, which may be large at the exploratory stage, this two-step analysis can lead to significantly incorrect results. Although LISREL allows the estimation of coefficients of the structural equations without the explicit calculation of factor scores (one-step estimation), most studies (83%) did not take advantage of this useful feature. Some studies even constructed the values of latent variables by simply aggregating indicators.

Measurement tests

Of the causal field studies using latent variables modeling, 50% (21/42) did not perform tests for both construct validity and reliability (studies which only reported Cronbach alpha [Cronbach 1951] are not counted as having conducted measurement tests, since validity is a critical issue in measurement). Concerns have been raised in the earlier MIS literature about measurement reliability and validity (e.g., Galletta and Lederer 1989; Grover et al. 1993; Jarvenpaa et al. 1985; Pinsonneault and Kraemer 1993; Sethi and King 1991). For example, Jarvenpaa et al. (1985) address the lack of internal validity in experimental studies.

Sethi and King (1991) provide a review of construct validity and reliability tests in MIS research. Straub (1989) compares instrument validation in MIS literature with that in reference disciplines such as the administrative sciences and concludes that MIS researchers are less inclined to validate their instruments. Similar concerns are voiced by Newstead et al. (1991) based on a 1970–1988 survey. The findings here show that this problem remains to be addressed. In the next section, the very assumptions of factor-analytic tests of reliability and validity are critiqued; however, the above observation suggests that empirical MIS research has not fully exploited existing measurement tools.

To summarize the major findings from the survey, first there is a compelling need for richer model development. A simplistic S-R view of relationships (as first observed by Cooper 1988) continues to prevail in the MIS literature, which ignores the justification of endogeneity and exogeneity as well as mechanisms that govern the relationship between two or more variables. A related problem is the direct adoption of models from the domains of organizational behavior and economics without the incorporation of MIS specific factors. Second, the primary reliance on factor analytic approaches for model representation and analysis is also problematic, since it may force a researcher to develop a model in accordance with the restrictive assumptions of the tool itself. This problem (discussed in detail in the next section) is more critical for the exploratory phase, since violations of causal assumptions which go undetected at this stage are unlikely to be detected at the confirmatory phase either. Third, while a realistic model of an MIS problem should involve the joint deployment of latent and measured variables, the paucity of studies following this approach indicates an excessive dependence on reference disciplines which use either purely latent or purely manifested modeling approaches. Finally, only half of the studies in the sample conducted tests of reliability and validity, in spite of the existence of a large body of methodology literature in MIS dealing with this issue.
Given the primary reliance on factor analytic approaches in the sample, it is important to assess the representation and measurement related limitations of factor analysis. These issues are addressed in the next section.

**Pitfalls of Reliance on Factor Analytic Approaches**

**Model representation**

Richer model building necessitates sophisticated and flexible representation of causal relationships. Although 83% of the field studies developing latent causal models used factor analysis, two of its key assumptions restrict the flexibility in model representation: all error terms are uncorrelated and the indicators are a realization of only the latent factors. Since these assumptions are not empirically tested, their violations and consequential distortions of the results go unnoticed. One study relaxed some restrictions on error terms (Jöreskog and Sörbom 1982), but factor analysis is still not general enough to include a wide range of causal relationships.

The second assumption is more critical. It implies that the direction of causality is from constructs to the indicators. This may be problematic in many cases. Consider a commonly encountered latent variable, "socioeconomic status" (SES), which is operationalized by measuring education level, income and occupation (Glymour et al. 1987). Casting this latent variable and its indicators in the factor-analytic framework, SES is taken as the exogenous variable (cause) that affects education, income, and occupation. However, it is not difficult to rationalize other causal relationships that are in direct conflict with the above model. In fact, a more convincing scenario may depict socioeconomic status as an outcome of education, income, and occupation (Glymour et al. 1987). Then the causal dependencies are the opposite of the factor model specification, with very different implications for estimation. Since causality implies an inherently asymmetric relationship between a cause and its effect, reversing the direction of causality results in a different model with the same set of variables. Similar analogies can be applied to the MIS domain. For example, MIS personnel expertise is often measured with education and experience as key indicators. It appears more intuitive to hypothesize that education and experience (among other things) lead to expertise, which is again the opposite of the causal representation required in the factor analytic world.

Another representational limitation arises out of the untested assumption that there are no causal links between the indicators of a construct. While this assumption leads to statistical simplicity, it is conceptually restrictive and statistically unnecessary. It represents a situation where, contrary to a basic tenet of philosophy of science, the tool dictates how the model is developed and represented. As an illustration, it is entirely plausible that the three indicators of socioeconomic status have some causal linkages among themselves (e.g., occupation determining income); however, the researcher cannot use such specification to satisfy the requirements of factor analytic methods. An example involving causal links between indicators from the MIS domain will be provided later in this paper.

We believe that we have been constrained by the representational limitations of existing research tools, and that by using a manipulative account and the justification of endogeneity/exogeneity, often the theoretical implications of a causal model may turn out to be in sharp contrast with the representation requirements of empirical research tools. Being able to represent a model according to theory without making additional assumptions is a critical element of discovering causal relationships. Returning to the analogy of exploration for natural resources, a simulation tool, which does not allow a researcher to fully represent a model connecting characteristics of a region to the likelihood of finding a particular natural resource, may predict a wrong area for exploration, in spite of a possibly correct theoretical foundation.
Causal Relationships

Representational requirements for emerging MIS theories

While the need for richer theoretical development has been stressed in this paper, the future appears to be promising in this regard. We are witnessing the emergence of sophisticated approaches to the study of interactions between technological and social structures (e.g., DeSanctis and Poole 1991; Orlikowski 1992; Orlikowski and Robey 1991). Through the deployment of adaptive structuration theory (AST), the interaction between technological and institutional perspectives is emphasized and focus is placed on the mechanisms (or instruments) governing the interactions between technology and social structures (DeSanctis and Poole 1991). This emphasis on mechanisms conforms to the non-Humean view.

The methodological sophistication required to use these concepts in empirical studies is higher than that provided by commonly used model representation techniques and analysis tools. For example, the operationalization of the interaction perspective advocated above may require technology and organizational factors to have bi-directional relationships (since they both affect each other, while in the technology imperative viewpoint, the causality goes from the technology to the organizational variables), which are outside the scope of currently used tools. A similar sentiment is expressed by Kaplan and Duchon (1988):

Often . . . studies do not proceed from an interactionist framework—one that focuses on the interaction between characteristics related to people or subunits affected by the computer system and characteristics related to the system itself.

Factor analytic tests of reliability and validity: are they reliable?

From the survey, it was found that the state-of-the-art instrument development and measurement techniques in empirical MIS research have followed Bagozzi (1977, 1982a) and Churchill's (1979) work in the marketing literature on reliability and validity of construct measurement. However, tests for assessing reliability and validity in Churchill's framework and elsewhere are based on factor models, and therefore share their limitations. For example, the typical summary statistic used for the reliability test is the Cronbach alpha coefficient (Cronbach 1951) or Bagozzi's (1981) reliability coefficient. Unfortunately, these coefficients themselves are consistent only when the untested assumptions of the factor-analytic model hold true. Similarly, tools for assessing convergent validity (e.g., Exploratory Factor Analysis [EFA], classification methods such as Principal Component Analysis [PCA]) and discriminant validity are also based on factor models. Even at the multi-method level of analysis in the confirmatory phase, the tests for convergent and discriminant validity (e.g., Confirmatory Factor Analysis [CFA] and the MultiTrait-MultiMethod [MTMM] approach) share the same limitations as the tests at the mono-method level. That is, these tests themselves can become unreliable without the researcher's knowledge under the circumstances described above.

In addition, MTMM (Campbell and Fiske 1959) or the reliability test of CFA may not detect a systematic perception bias between different methods. In many MIS problems, measuring the perception bias may be an important step in better understanding the phenomenon of interest. For example, the perception of the quality and functionality of a newly developed system may be systematically different across the developer and the user groups. Unfortunately, with such systematic bias, correlations in the MTMM matrix can still be significantly positive, falsely indicating agreement between the different respondent groups. Of course, the reliability test in CFA may suggest a lack of reliability. But the latter may be attributed to a number of factors, only one of which is perception bias. Should we discard the item on the basis that it is unreliable? We argue that, on the contrary, detecting systematic perception bias may enrich the theory, since it may indicate the existence of a more complex mechanism governing the problem of interest. One study (Straub et al. 1993) recommends that in such cases a construct should be refor-
mulated as two separate constructs (when there are two methods). For example, if users perceive heavy IT usage (while the true usage is low), the suggestion is that "it may be desirable to reformulate system use as two entirely separate and separable constructs, i.e., perceived system use, a construct with its own attributes and relationships, versus actual system usage" (Straub et al. 1993).

How Does LISREL Help?

It has been suggested that LISREL combines the significant methodological developments in various branches of social sciences: path analysis in sociology, simultaneous equation systems or structural equation systems in econometrics and confirmatory factor analysis in psychometrics (Hughes et al. 1986). The focus of the present study is on two aspects of LISREL: its advantages over factor analysis and its model modification feature. Unlike factor analysis, LISREL considers measurement errors in the estimation process, whereby items measuring a construct (i.e., the measurement model) are assessed within the context of the theoretical (structural) model.

However, if there is any latent variable in the model, LISREL inherits the representational limitations of factor analysis (e.g., the direction of causality between constructs and indicators, no causal links between indicators, etc.). In order to ensure identifiability, LISREL also makes certain untested assumptions such as errors being uncorrelated among themselves and with the predictors in the structural and measurement models. LISREL also assumes independence of observations, making itself inappropriate for the analysis of dynamic (longitudinal) models, except some simple ones (Aigner et al. 1984). These assumptions involve more than convenient statistical simplifications and are intricately linked with the hypothesized causal model. Given that LISREL is a confirmatory tool, these assumptions would not be a problem as long as (1) the theory suggests a model that conforms to the factor analytic representation and (2) empirical evidence shows that the modeling assump-

LISREL takes advantage of model fitting techniques in exploring alternative models. For a given set of data, LISREL maximizes the fit between data and the model. If the model does not fit well, a fixed parameter or an equality constraint is relaxed. Selection of a
Causal Relationships

parameter to be relaxed is done in a way such that it increases the overall fit. A modification index ensures that this requirement is satisfied (Sörbom 1989). While several limitations of this approach have been pointed out (Glymour et al. 1987), such criticism is primarily relevant to model explorations at the confirmatory stage. Our interest, however, lies in whether LISREL's modification principle can be used to aid theory development in exploratory research. Since LISREL maximizes the fit only within a given set of variables, it cannot provide any guidance as to whether new variables (and hence new relationships) should be introduced. In a new field, the omission of key phenomena (e.g., incentives in MIS studies) and their associated variables may be detrimental to new theory development. An exploratory tool should contain provisions to account for such possibilities.

Searching for a New Approach to Exploratory Research

While we are in total agreement with the prescription of rigorous confirmatory research, we believe that exploratory research is at least equally important in MIS. Existing research approaches have been shown to have several limitations relating to the representation and exploratory analysis of causal models, which when ignored may carry over to the confirmatory stage. A desirable approach and its tools for exploratory research should allow flexible representation of causal models with minimum conceptual and statistical restrictions. Many tool related limitations mentioned earlier arise out of their parametric nature. TETRAD, a non-parametric modeling tool (Glymour et al. 1987; also see Glymour and Spirtes 1988), appears promising in this regard.

TETRAD represents a proposed causal model as a labeled directed graph. Such a graph uniquely determines the structural equations of the statistical model, while undirected paths represent correlation without causality (e.g., correlation among error terms). For example, consider three normalized variables X, Y, and Z. Suppose a hypothesized causal model is given as

\[ X \rightarrow^a Y \rightarrow^b Z \]

where \( a \) and \( b \) are coefficients. If the two hypothesized causal links are true, then regardless of the values of \( a \) and \( b \), the partial correlation between \( X \) and \( Z \) with respect to \( Y \) must be zero. This is referred to as vanishing partial correlations (VPC) in TETRAD. When there are four or more variables, it is more useful to consider the notion of TETRAD equations. With four variables, there are six possible correlations between pairs of variables, and only three non-equivalent products of correlation pairs which involve all four variables. Under certain symmetry conditions, these products are equal and the equality of three correlation products leads to three TETRAD equations. One can theoretically show that when VPCs for any four measured variables hold, they also imply that the TETRAD equations are satisfied. However, the converse is not true.

The strategy of TETRAD in identifying causal relations is to determine the VPCs implied by the hypothesized model and to examine the sample correlation matrix to determine if the VPCs and TETRAD equations indeed hold in the data. If they do not, then the theory leading to the hypothesized relationship is falsified. TETRAD also determines patterns which hold in the data but were not specified by the researcher, presenting them as new candidates for consideration. This takes the researcher back to the theory building stage, where the initial model may have to be modified or enriched based on a new or additional theoretical rationale. Although TETRAD is based on sample correlations, TETRAD equations distinguish between the direction of causality. Consider a measurement model I, in which a latent variable manifests itself through a set of indicators, whereby the direction of causality is from the latent variable to its indicators. Suppose we now reverse the direction of causality in model I, whereby the measured variables are posited to cause the latent variable (say, model II). Appendix B demonstrates
that these two models have different implications for TETRAD.

Advantages of TETRAD

Non-parametric analysis: Unlike factor analytic approaches, there is no statistical parameter estimation for a hypothesized causal model in TETRAD. Thus, TETRAD is free of many untested statistical assumptions found in existing research tools, which are more suited for the confirmatory phase (provided their assumptions are not violated). This reduces the risk of a transition to the confirmatory stage without detecting causal violations of confirmatory tools.

Flexible representation: TETRAD allows direct causal relations between measured variables, as well as linkage between latent and measured variables in any direction. It thus provides representational flexibility. Examples from MIS and other domains are provided in this paper suggesting that such linkages are likely to be encountered in empirical research. Moreover, TETRAD clearly distinguishes (unlike factor analytic approaches) between causal linkages among indicator variables and unexplained error correlation, which are different issues both conceptually and statistically.

Linking two research phases: Model modification in TETRAD is based on the principle that "ceteris paribus, the best model is one in which any constraints (patterns) among the population correlations are also present in the model (independent of values of any free parameters); conversely, that no constraints are implied by the model which are not also present in the population" (Glymour et al. 1987). It attempts to modify a model such that the discrepancy between the patterns in the data and those implied by the hypothesized model is minimized. An important model modification related advantage of TETRAD involves its ability to point out missing variables and to indicate (based on heuristics) whether a measured or latent variable is appropriate.

Shortcomings of TETRAD

Several limitations of TETRAD have been pointed out (Bollen 1990). TETRAD equations are derived under the assumption of multivariate normality of observed variables and may lead to misleading results when the assumption is violated. Second, outliers can change the magnitude of TETRAD differences and lead to incorrect model selection. Another problem recognized by the developers of TETRAD involves multiple testing on each model (Glymour et al. 1987). Bollen (1990) has recommended remedies for each of these problems. For example, he provides a statistic for outlier detection, an approach to assessing asymptotic variance in the case of non-normal distributions, and suggests a Bonferroni adjustment and a statistic to mitigate the multiple testing problem.

Hunt (1989) suggests some additional shortcomings of TETRAD. He observes that for small correlations, TETRAD differences may be very small, and hence may be falsely considered as zero. However, it should be noted that TETRAD tests whether the residual of a TETRAD equation is "statistically" zero, and not whether it is numerically small. Hunt has also pointed out a limitation of TETRAD's model modification procedure: "[T]he tests for adding edges and correlated errors are performed in a univariate manner. It is thus possible that the particular group of additions could be stepwise optimal yet not be the overall optimal group of additions." Bollen (1990) has suggested a way to mitigate this problem by designing a simultaneous test of whether all TETRAD equations implied by the model are true.

Hunt also notes that TETRAD does not contain provisions for specifying correlations between exogenous variables in multiple regression models and hence cannot help in model modification for exogenous variables. However, by their very definition, exogenous variables cannot be caused by other variables in the model. Therefore, while it is true that TETRAD does not help in causal elaboration for exogenous variables, to try to do so would violate the definition of exogeneity. The most important issue
with exogenous variables is whether they are really exogenous to the modeler’s world. A specification test (Hausman 1978) accomplishes this objective and has been used to show the endogeneity of input variables such as IT investment by (Barua and Lee 1997).

Examples highlighting TETRAD’s advantages

Several cases where TETRAD was found to be a promising tool for exploratory research are discussed and an explanation is given for how such cases may arise frequently within the MIS domain.

Causal linkages between indicators: While model specification and subsequent analysis become simpler when there is no causal linkage between indicators, it is important to test whether such links exist in a specified model. Consider a model proposed and tested by Adams et al. (1992). The ease of use of a technology and the usefulness of a technology are independent latent variables, while usage of IT is the dependent latent variable. The indicators of ease of use are “easy to learn,” “clear and understandable,” “easy to become skillful,” and “easy to use.” The indicators of usefulness are “work more quickly,” “job performance,” “increase productivity,” and “makes job easier.” While causal relationships between indicator variables are prohibited in factor analysis and LISREL, justification can be provided for several causal links among the indicators in the above model. For example, a “clear and understandable” technology should make it “easy to learn,” ceteris paribus, which in turn should make it “easy to become skillful” with that technology.

To argue against the inclusion of these intuitively appealing additional links, one should justify from a theoretical standpoint why these specific links should not exist; further, during the exploratory phase analysis, empirical evidence should be obtained to support such a position. We consider it as the process of eliminating competing hypotheses that (1) clarity and understandability make it easy to learn and that (2) ease of learning increases the ease of becoming skillful. Unfortunately, such a specification is prohibited in factor-analytic approaches, and if LISREL is used at the confirmatory stage, it will also not take the linkages into account (which would not be a problem provided the exploratory stage research shows that such links do not exist). Using a series of simulation studies with sample sizes varying from 200 to 2,000, it has been demonstrated that TETRAD is well suited at the exploratory phase to handle models with causal links between indicators (Glymour and Spirtes 1988; Spirtes et al. 1990).

Linkages among indicators across constructs: In a model of industrial and political development, it was hypothesized that industrial development (measured by GNP, energy consumption, and labor force diversification) causes political development (measured by an index of executive functioning, political party organization, an index of power diversification, and an index of political representation) (Costner and Schoenberg 1973). However, this model was not supported by the data. Interestingly, starting with the initial model, TETRAD suggested direct causal links among indicators: from political party organization to power diversification, and from GNP to executive functioning.

Returning to the MIS example above, being skilled in a technology, a user should be able to work more quickly, implying a causal linkage between indicator variables across different constructs. This would be considered a major violation of the assumptions of existing approaches. As aptly pointed out, one question or competing hypothesis that the researcher should address is whether the linkage(s) among indicators of different constructs are a surrogate for the posited relationship among the factors (Glymour et al. 1987). When such linkages are present, statistically it is not difficult to obtain consistent estimates of the model parameters, although they are beyond the scope of the existing approaches. A more fundamental question is why such a linkage is being observed. Is it the case that the relationship between indicators across constructs is stronger than the relationship...
between the constructs themselves, when in fact the theory was posited as a relationship only between the constructs?

**Direction of causality:** In measuring socio-economic status (SES), the traditional operationalization where the direction of causality points to the indicators from the construct was used (Majidson and Sorbom 1982). Earlier the argument was made that, for the SES and many other constructs, there is strong theoretical rationale to support the opposite direction of causality. Majidson and Sorbom's model estimated with LISREL leads to a poor fit (Glymour et al. 1987). The analysis by Glymour et al. of the same data with TETRAD suggested links from manifested variables to the latent factor. This is an example where the theory supports a particular causal model, but where the factor analytic representation requirements force the researcher to reverse the direction of causality.

**Detecting anchoring and adjustment:** A correlated errors model was used for a factor "Authoritarianism-Conservatism" with five indicators measured on a five point scale from "strongly disagree" to "strongly agree" (Schoenberg and Richtand 1984). While such a model was developed in conformance with factor analytic modeling, the analysis of this data with TETRAD implied causal links between the indicators (Glymour et al. 1987). These causal links were interpreted as indicative of Kahneman and Tversky's (1979) anchoring and adjustment problem, where a respondent's response to one indicator item affects the response to the next item (Glymour et al. 1987). Based on the TETRAD output, Glymour et al. were even able to predict the possible order in which the questions were asked. This is a promising feature of TETRAD which can be used to improve the measurement of latent variables in a field study without an extensive inventory of thoroughly tested instruments.

**Introducing new variables:** This capability is highlighted with an example involving SAT scores (Glymour et al. 1987). Given the objective of predicting a given year's SAT scores and the availability of data (SAT scores for seven consecutive years), TETRAD suggests a model with a latent variable (labeled "test taking ability") in a particular year, which affects that year’s test scores as well as next year's test taking ability. Of course, if additional data were available, test taking ability itself could be modeled as a dependent latent variable. The advantage here is that TETRAD does not favor one type of variable over the other and offers a heuristic basis to guide when a new latent variable should be introduced.

**Proposed Procedure for Empirical Research in MIS**

The previous observations and discussions on generating, representing, enriching and exploratory analysis of causal models lead to an integrated approach for the conduct of empirical research in MIS. The following steps are proposed.

**Step 1:** The focus is first placed on building a theory of the problem of interest. We suggest adding several new elements, including the conceptual assessment of exogeneity of predictors in the theoretical model, a manipulative account of proposed relationships, as well as a consideration of enriching the model with characteristics mentioned earlier. While the exercise of justifying exogeneity may appear to be a mere statistical minutiae, it actually reflects the researcher's conceptualization and rationale of the theoretical model itself. Having formulated a baseline model, the researcher must ask the question: Can we theoretically justify the predictors in the current model as exogenous? A number of examples have been provided where variables that are assumed as exogenous can be theoretically supported to be endogenous.

The conceptual justification of exogeneity and endogeneity must be complemented by invoking a manipulative account to assess the direction of causality rather than being guided by limitations of modeling tools. The researcher should identify the variables for which one can set the levels at least in principle. While this
Causal Relationships

may appear somewhat trivial at a first glance, a quick application of the principle to the SES and other constructs will show that the conventional measurement model may not always be theoretically supported by a manipulative account. If we ask which variables we can manipulate directly in the SES model, the somewhat obvious answer is education, income and occupation, and not our standing in society. Similarly for developer or user skills, we can manipulate indicators such as education, training, and experience rather than development or usage skills. In other words, in these cases a manipulative account would suggest that the direction of causality is from the indicators to the latent variables. It is important to note that we are not suggesting that every latent variable be considered as a dependent variable caused by measured variables. For example, in measuring user satisfaction, it is only logical to assume that the latent variable satisfaction will lead to the measured indicators. The approach presented here lets theoretical rationale (rather than the requirements of specific tools) decide the direction of causality.

This is also an appropriate time to consider whether the model just specified could be enriched substantially by incorporating one or more of the characteristics of IT, organization, business processes and incentives. Such enrichment is important in specifying the mechanism or organism in an otherwise simplistic S-R model, as seen earlier in the reengineering example. Which specific factors should be taken into account depends on the problem at hand. For example, if the impact of GDSS on workgroup productivity is being considered, market characteristics are clearly unimportant, while the characteristics of incentives (e.g., group versus individual contribution based rewards) would appear to be an essential element of the model. It should also be noted that what appear to be exogenous variables may become endogenous when the above characteristics are brought into consideration through a manipulative account, as witnessed in the examples of education level and top management involvement.

While the motivation to consider issues such as endogeneity/exogeneity and incentives stems from the economics literature, they are equally applicable to the organizational domain. Further, we are not calling for economics as the basis of modeling; rather, we are suggesting a set of principles which should be equally useful to both economic and organizational approaches in MIS.

Step 2: This involves the representation of a preliminary causal model. Following step 1 may result in a model that is outside the domain of factor analytic approaches (e.g., a model where measured variables are postulated to impact a latent variable and where there may be linkages between indicator variables). However, the additional complexity can be handled comfortably with existing statistical approaches both at the exploratory and confirmatory stages. Further, while Churchill's procedure and all other factor analytic approaches assume multi-item measures in conformance with the conventional psychometric model, in this procedure, we do not require any restrictions on the causal relationships. In other words, the researcher should feel free to choose both latent and manifested variables.

If there are latent variables in the model, as would be expected in most cases, then sample items (indicators) are developed. Two possible scenarios deserve special attention: Is there any causal dependence between the indicators that can be supported with a theoretical rationale? For example, the rationale we presented regarding the links between indicators in the technology usage model (Adams et al. 1992) violates conventional factor analytic modeling assumptions, but does not present a problem in our approach. However, we require that such linkages be theoretically justified.

The second situation involves unintentional causality between indicators resulting from anchoring and adjustment on the part of the respondents. This possibility should not be overlooked, since MIS researchers often use new instruments given the lack of a cumulative tradition in a relatively young field. This is more subtle than the case where the researcher has conceptually justified links between indicators.
As discussed earlier, TETRAD can help detect such anchoring and adjustment bias.

**Step 3:** At this stage, sample data is collected. A pilot study is important to assess if anchoring and adjustment effects are present. If we rely on secondary data (which is common in economics-oriented studies), the steps involving construct measurement and testing may be avoided. However, we must ensure that the secondary data is appropriate for our model, and should be checked for accuracy and potential bias. Further, as has been emphasized, any realistic model will most likely require a mix of latent and manifested variables.

**Step 4:** In order to avoid a priori assumptions during the exploratory stage and to represent a model based only on theoretical rationale, we propose using TETRAD instead of the conventional factor models. The main objective here is to assess if the preliminary model is adequately supported by the data. There are two possibilities: rejection of the initial model or absence of an empirically sound model.

If the initial model is rejected, and if TETRAD suggests the necessity of new variables (i.e., an increase in the scope of the model), then we return to step 1. There are several possible scenarios here. First, the researcher may have to enhance the theory by identifying more agent, team/workgroup, process, incentives, IT, or organizational characteristics. This step involves more than adding extra variables to an initial model. More often than not, this step will result in additional relationships arising from deeper insights into the processes connecting the variables of interest. Relevant examples involving management style and incentives in the GDSS domain were provided. The extra relationships are not isolated additions to the initial model; rather, they are intricately linked through common variables with the initial set of relationships. TETRAD provides guidance as to whether the new variables should be manifested or latent, and this must be augmented by the researcher’s prior knowledge of the domain of interest. Thus, we believe the use of TETRAD along with this framework will help address the call for a richer “dialogue” between theory and data (Smith 1982; 1989).

It is also possible that TETRAD will suggest additional or different causal links between existing constructs and indicators. For example, TETRAD may suggest links between the indicators belonging to different constructs. Such links represent competing hypotheses which had not been considered during the initial theory development. The researcher must then justify whether such linkages are conceptual or measurement related (e.g., the order in which the questions were asked).

If no empirically sound model is found in the TETRAD analysis, then it is possible that the data are unreliable. In that event, reliability tests based on the initial model should be performed. We can find items that are not reliable and return to step 3 for new data collection.

If the outcome of applying TETRAD suggests that no additional variables be added (i.e., either the initial model is supported or a better model can be derived by modifying causal relationships among existing variables) go to step 5. When TETRAD suggests a better model with existing variables, we must go to step 5 only after revisiting step 1. That is, we must be able to find a theoretical rationale or justification for any new link that TETRAD might suggest. For example, Glymour et al. (1987) were able to attribute causal linkages between indicators of the “Authoritarianism-Conservatism” construct to an anchoring and adjustment effect.

**Step 5:** Here we collect data for the confirmatory stage. As has been emphasized (Churchill 1979), the multi-method approach may have several advantages over the mono-method process at this stage.

**Step 6:** Given that reliability tests and the MTMM method may fail to identify systematic cognitive bias across methods, we should apply appropriate pooling tests on the model suggested at step 4. If there is a systematic difference among methods, we should incorporate the perceptual differences as causal vari-
ables (as suggested by Straub et al. 1993) and return to step 4. Otherwise, we go to step 7.

Step 7: This step involves model specification at the multi-method level of analysis. We purify measures if deemed necessary based on tests of reliability and validity.

Step 8: One major objective of causal modeling is to test (verify or falsify) causal hypothesis. However, TETRAD only indicates possible causal linkages among variables and does not provide any estimates of parameters in the model. Thus, we have to employ estimation procedures for testing our hypotheses. At this point, we will have a system (or several candidate systems) of relationships. If latent variables are present, then we have both measurement models and structural equations. Also, as discussed earlier, a realistic model often turns out to be a set of structural relationships. The estimation tools to be used at this stage depend on the model at hand. For example, the proposed procedure may result in a model out of LISREL’s scope. For instance, there may be direct causal links among indicators. Similarly the statistical independence among error terms across constructs or exogenous variables (e.g., time lagged observations) may be violated. In such events, the model should be estimated with appropriate econometric techniques which ensure that the estimators satisfy requirements such as consistency, efficiency and unbiasedness (Judge et al. 1988).

The scope of TETRAD in the proposed approach

There are two key elements in the proposed approach: developing richer models and using flexible and powerful tools to operationally represent and analyze such models. TETRAD allows the researcher to represent a model and conduct exploratory analysis without imposing restrictive assumptions about causal links, error terms, and the latent or manifested nature of the variables involved. It can also offer valuable guidance by suggesting whether a proposed set of relationships is adequately supported by data, in detecting measurement related problems such as respondent bias (as seen in the Authoritarianism-Conservatism example), as well as in deciding whether new variables should be brought into the analysis. However, it is incumbent upon the researcher to develop richer models based on a powerful conceptualization of the problem and a carefully articulated theoretical foundation. The suggestions offered here regarding characteristics of MIS specific factors, considerations of exogeneity/endogeneity, and a manipulative account of causality provide a starting point in this direction.

Data requirements for richer models

Richer models incur the cost of additional data collection, in the form of a larger sample size and/or extra variables (indicators in the case of latent variables). While adding variables to a model takes away degrees of freedom, the increase in the sample size necessary to compensate for this loss is not substantial, except in the unlikely event of adding a large number of new variables. A more critical concern is that, with new variables, questionnaires become longer and the response rate is expected to become smaller. Thus, there is certainly a tradeoff between richer models and the burden of additional data collection. Based on our survey of the MIS literature, we believe that the marginal benefit of richer models in MIS is very high and that the resources required for additional data collection may be more than offset by the corresponding benefits. At the very least, a researcher can initially develop a rich model, assess the cost and the potential benefit of analyzing the full model versus a simpler version, and make a decision regarding model richness with the knowledge of the shortcomings of using a simpler specification. For example, if there is a theoretical basis to believe that a variable is endogenously determined within a rich model, the researcher may sacrifice too much realism and accuracy by assuming the variable to be exogenous and proceeding with a simplified analysis of the model.
Conclusion

Being a relatively young discipline is a mixed blessing for MIS. On the one hand, many researchers in the field have indicated that we face the problem of a paucity of a well-developed and shared body of knowledge, and that of inadequate methodological rigor in the conduct of empirical research. On the other hand, we believe we have an exciting opportunity to redesign the process of developing, representing, analyzing, and enhancing MIS theories. Discovering and representing causal relationships is a focal theme of this endeavor. While discovery usually has an implication of luck or chance associated with it, we have heavily emphasized that our study and recommendations are focused on discovering relationships aided with a strong conceptual or theoretical foundation. Using the analogy of exploration for natural resources, we suggested that a richer theory and its resulting model enable the researcher to focus only on specific geographical areas with a high likelihood of success. Our call for the explicit justification of exogeneity and endogeneity of constructs, manipulative accounts of relationships, as well as the consideration of factors such as incentives, IT, and organizational and business processes serves to highlight this focus on enriched model building at the exploratory phase. These extensive considerations, which we have argued to be more thorough than the current level of model building, arise before any data is collected.

Based on philosophy of science, developments in the field of experimental economics, and sociology, some ways of improving approaches to developing causal relationships were suggested. Specific areas which require close attention, both at the theory building and model representation and exploratory analysis phases were pointed out. For example, we must exercise caution in ensuring that endogenous constructs or variables are not used as predictors; it is imperative that we take the time during the model development phase to explicitly justify why we believe the predictors to be exogenous within the problem domain of interest. This is intricately connected with the mechanisms that govern the relationships between variables of interest and often a simplistic S-R conceptualization can be transformed into a richer S-O-R specification by incorporating the mechanisms themselves within the model, as seen in the example of IT productivity. Further, the theoretical justification of exogeneity must be complemented with statistical tests of exogeneity/endogeneity after the data have been collected.

In a similar vein, assumptions regarding the behavior of various agents in a model have been made explicit. Agent behavior depends, among other things, on the incentive system. This is an area that relates back to the "why" and "when" aspects of model building and deserves more attention in the literature. Since the researcher cannot randomly assign the values of independent variables to the participants in the study, s/he must consider the behavior of the participants (as seen in the examples of education level and income and top management involvement and success) in the model. Such careful modeling, along with a manipulative account of causality, will help develop a strong theoretical foundation for discovering useful causal relationships. It is also important to note that considerations of exogeneity/endogeneity, a manipulative account, and the incorporation of incentives and other factors are not isolated recommendations; rather, a manipulative account involving how factors such as incentives affect behavior results in a clear understanding of exogenous and endogenous variables in a model.

In representing causal relationships, we have argued that it is neither conceptually sound (from the perspective of philosophy of science) nor operationally necessary to develop a theory in conformance with the restrictive requirements of factor analytic models. Restrictions, such as the lack of causal linkages between the indicators of a construct, may often turn out to be difficult to satisfy from an operational standpoint and also artificial from a theoretical viewpoint. Our recommendation is that the researcher should represent a model along the lines of the theory. Exploratory tools like TETRAD can analyze a wide variety of linear causal patterns and any mix of latent and man-
Causal Relationships

...tested variables without making unnecessary assumptions and imposing statistical restrictions. It should be noted that TETRAD and LISREL are not being compared, since the two are applicable at two different phases of empirical research. Our concern with LISREL is that violations of its assumptions are unlikely to be detected at the exploratory stage and that a researcher may unknowingly use LISREL with a model that is actually beyond the scope of LISREL.

This exploratory research approach should be flexible to accommodate the fact that the initial theories may not be infallible and the tools chosen should help point out discrepancies between the theory and the data. Of course, as emphasized throughout the paper, a rich theoretical foundation will lower the likelihood of a theory being rejected completely. In order to integrate the two phases of research, we must go beyond testing the initial model; if the initial model fails, we have to return to our theory, reassess its applicability, possibly modify or enhance the rationale, and repeat the empirical analysis.

One of the interesting issues that warrants additional investigation is the link between extending theories and empirical testing. Developing new theories involves scholarship and creativity, which are challenged when data fail to support hypotheses derived from proposed theories. TETRAD and other non-parametric tools have the potential to offer guidance to the researcher. When properly used, such guidance can be complementary to the researcher's domain knowledge and contribute to the creation of new theories. Future research in this area should focus on how and where these tools should help the researcher in enriching or modifying preliminary theoretical developments.

Yet another interesting avenue for further investigation is the comparison of various tools for exploratory research. While TETRAD appears to be promising in this regard, it is not the only exploratory tool. Our preference for TETRAD is primarily attributable to its non-parametric nature. Hence, we believe that any non-parametric tool should be considered as a potential candidate for the exploratory stage, and should be tested against TETRAD.

Research methodology is critical because it can help correctly reject (or not reject) hypotheses derived from theories. In addition to theory testing, methodological guidelines should also help develop new theories. Many useful recommendations (e.g., different approaches to research, statistical issues of power, validity, etc.) have already been made in the MIS literature regarding the process of conducting empirical research. Our paper complements these recommendations by focusing on a richer foundation for model development, and on issues relating to model representation and exploratory analysis.

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References


Causal Relationships


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Appendix

Classification of Research Methodologies

The classification scheme for research methodologies in Table A1 is as follows:

**Non-causal model:** Involves a study that does not propose any testable hypothesis.

**Pure manifested modeling:** The variables of interest in the proposed causal model are all manifested (i.e., directly measured). Research in economics of information systems follows this tradition.

**Pure latent modeling:** The variables of interest in the proposed causal model are all latent (i.e., measured through indicators).

**Measurement test:** Whether reliability and validity tests such as convergent and discriminant validity are conducted. If convergent and discriminant validity tests are reported at the mono-method level, we conclude that the study conducted measurement tests.

**Two-step estimation:** If factor (construct) scores were obtained from indicators through factor analysis, and if the structural relationships between constructs were tested separately, the study is classified as using the two-step estimation procedure.

**One-step estimation:** If the structural (causal) and measurement models are considered as one system of equations (with errors-in-equation), the study is classified as using the one-step estimation procedure.

Comparison of Models I and II

Model I (traditional factor model) is represented as

\[ x_i = a_{ij} F + e_i, \quad i = 1,...,n \]

where \( x_i \), \( F \), and \( e_i \) represent the \( i^{th} \) indicator, the latent variable, and the error associated with the \( i^{th} \) indicator respectively. Glymour et al. (1987) show that the correlations \( \rho_{ij} \) for this model are given as:

\[ \rho_{ij} = a_{ij} \rho_F \sigma_e^2, \quad i \neq j \]

\[ = a_{ij} \sigma^2_F + \sigma^2_e, \quad i = j \]

where \( \sigma^2_F \) is the variance of \( F \), and where \( \sigma^2_e \) denotes the variance of \( e_i \). Therefore,

\[ \rho_{ij} = \rho_{ik} \rho_{kl} = \rho_{il} \rho_{jk} \neq 0 \] (1)

Now let us show that model II (reversed factor model) has different implications for TETRAD. This model is represented as:

\[ F = b_i x_i + e_i, \quad i = 1,...,n \]

In matrix notation, we have:
\[ JF = BX + E \]

where \( J = (1, 1, \ldots, 1) \). Let \( \text{Exp}(X) \) and \( T \) denote the expectation of \( X \) and error covariance matrix respectively. The correlation matrix of this model is given by:

\[
\sum_{xx} = \text{Exp}(XX') \\
= \text{Exp}((B'JF - B'E) (B'JF - B'E)') \\
= \text{Exp}(B'JJB'FF + B'EEB'B' - B'EE'B'B'F - B'JE'B'F) \\
= B'JJB'B' + \sigma_F^2 + T
\]

\[
\rho_{ij} = 0, \quad i \neq j \\
= \sigma_i^2 / b_i^2 + \sigma_e^2, \quad i = j
\]

Comparing (1) and (2), it is evident that the two models are not equivalent.

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