Tutorial: Causal Modeling and Patient Satisfaction

Dale N. Glaser and Barbara Riegel

Causal modeling is used in a variety of sciences because it allows exploration of complex relationships among several variables simultaneously. Although not used extensively in health care as yet, causal modeling could be helpful, given the complexity of the current health care system. The purpose of this article is to provide a general introduction to causal modeling and the syntax used in developing and testing a model. To illustrate the method, a sample model is tested using a combination of hypothetical and actual patient satisfaction data.

Key words: *causal modeling, latent variable analysis, patient satisfaction*

Human behavior is infinitely complex and researchers have struggled for decades to find the best way of describing, explaining, and predicting actions. Inferential statistics such as analysis of variance may be helpful if, for example, the researcher is interested in determining how a certain treatment (e.g., medication) influences a particular outcome (e.g., blood pressure). Human behavior, however, is typically not so straightforward. In fact, any phenomenon becomes increasingly more interesting if other relevant factors are examined in concert. Such factors may include, but are not limited to: (1) psychological variables (e.g., locus of control, hardiness, perceived stress), (2) physiological factors (e.g., catecholamine levels), (3) behavioral factors (e.g., risky lifestyle), and (4) contextual variables (e.g., time of day or work reporting relationships).

Causal modeling is a statistical technique for examining models in which several variables are considered simultaneously. The purpose of this article is to introduce the concept, the technique, and the inter-

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pretation of causal modeling to the new user. In other words, this article is an introductory primer to causal modeling. As a way of demonstrating its usefulness, the technique is applied to health care and issues of quality. A model of patient satisfaction is hypothesized and tested using a combination of hypothetical and actual data.

Structural equation modeling (causal modeling) is a relatively new technique that has generated a great deal of interest because of its capacity to explore problematic or mathematically impossible puzzles. Structural equation models are simply theoretical models of relationships among variables.[1] In the past, researchers interested in testing multiple relationships might have used one of two related techniques: regression analysis or path analysis. Regression analysis and path analysis are related techniques, as both use correlational data. Regression analysis is a technique that uses categorical or continuous level variables to predict a single outcome variable.[2] Generally, this technique involves the entry of a select number of predictor variables that are thought to be possible predictors of the outcome.

If the investigator has an actual model in mind, path analysis might be used. Path analysis can only be used if the model progresses in a linear, sequential fashion (e.g., one variable causing another). Path analysis is a method for studying the direct and indirect effects of variables thought to cause subsequent variables. Of course, once the factor preceding a variable is identified, then the variable itself becomes an outcome or an effect.[3]

Both regression analysis and path analysis have significant limitations. In regression analysis, a single variable must be chosen as the outcome. As described above, it is easy for any budding theorist to postulate a variety of causes and levels of outcomes. In fact, it is far more difficult to identify a single outcome variable. In path analysis, each relationship must be assumed to progress in a linear fashion, a commonly untenable assumption in everyday life.

Causal modeling allows one to test models with multiple outcome variables and those in which relationships are thought to go in both directions. For example, social support has been shown to decrease emotional stress.[4] But emotional distress has also been shown to decrease social support. Because causal modeling is so useful in mimicking reality, it has been used widely in the sciences (e.g., economics, psychology, sociology, nursing, behavioral medicine). Several recent publications have used this method to investigate group success or failure and its effect on job satisfaction and organizational commitment[5]; consumer satisfaction and perceived quality[6]; participative decision making and job-related strain[7]; job performance, job satisfaction, and turnover[8]; and organizational characteristics, perceived work stress, and depression.[9]

Causality

It is not the intention of this article to clarify the reasoning behind the term *causal* or the controversy that surrounds the use of the term. As James, Mulaik, and Brett point out in their classic text, *Causal Analysis: Assumptions, Models, and Data,* "Causality is a complex topic, beset by controversy because of metaphysical and epistemological differences among philosophers of science."[10(p.13)] One of the major arguments against presumptions of causality when employing such techniques is that any technique using correlational data cannot aspire to causality. Mulaik counters that argument with this:

> These experimentalists claim everyone knows (or should know) that correlation does not imply causation. We may say in rebuttal that, whereas correlation does not imply causation, it is also true that causation implies correlation. It is this which makes the testing of hypotheses about causation possible with correlational data.[11(p.23)]

Whether one views causality as a product of "functional relations,"[10] "probabilistic causality,"[11] or "deterministic relations,"[12] the prevailing notion is that (1) causal analysis is contingent on assumptions about causal direction and (2) these assumptions are empirically or data based. The last point is critical. Guided by prior research and empirical data, the researcher develops and tests a model that specifies causal direction. Hayduk argues that social scientists typically think of one thing as influencing another and there is no reason to abandon causal statements.[1]

Terminology

The reader of publications using causal-modeling techniques must become familiar with a new language unique to these applications. That language will be taught using an example drawn from a hypothesized model (Figure 1) of patient satisfaction. The model, based on dummy data, is for illustrative purposes only.

The initial step in applying causal modeling is to develop a *model* that delineates specific relationships among a host of interrelated variables. It is important that the model be empirically based, as causal modeling is ideally a technique for confirming a theory. The validity of the model is reinforced through the inclusion of prior research in which the proposed relationship or relationships were demonstrated. For example, in the development of the consumer satisfaction or perceived quality model, Gotlieb and colleagues investigated a variety of relationships (e.g., between perceived situational control and satisfaction and between expectations and satisfaction) for the purpose of establishing an empirical foundation for their hypothesized model.[6]

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Causal modeling can be used in an exploratory manner, however. If a researcher is investigating an area with little empirical verification, he or she can develop a model based on hypothesized relationships among the model variables. In this case, experience and observation would guide model development instead of theoretical evidence. The model shown in Figure 1 is an exploratory model.

Causal modeling involves the analysis of *latent variables*. Latent variables are pure unidimensional

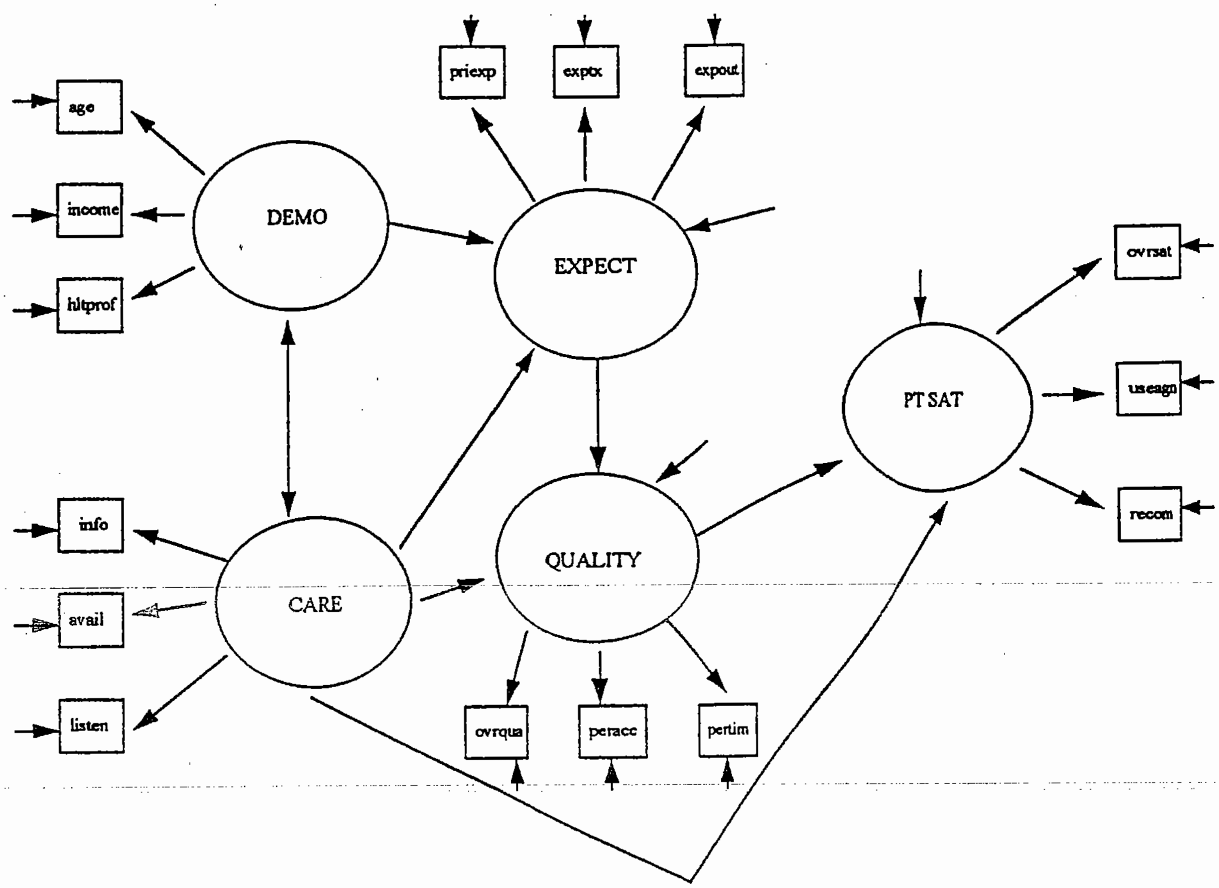

Figure 1. Patient satisfaction model.

concepts or constructs.[12] Such variables typically vary in their degree of abstraction. For example, "emotion," a variable often studied by psychologists, is an abstract construct that requires definition and operationalization before it can be used in a causal model. However, a latent variable such as "economic status" may be more easily used in a causal model.

Latent Variables

Latent variables can be characterized as *exogenous* and *endogenous*. If a variable has a cause that lies outside of the model (i.e., the variable acts as a cause and not as an effect), it is described as exogenous.[1,12] In the model shown in Figure 1, demographics (DEMO) and care received (CARE) are the exogenous variables. We acknowledge that there may be factors that cause or influence the exogenous factors in this patient satisfaction model. However, as this model is solely exploratory and pedagogical in nature, we will call these two variables exogenous.

Endogenous latent variables are those that are hypothesized to be determined or caused by variables within the model (i.e., directly caused or influenced by any of the other variables).[1,12] Patient expectations (EXPECT), perceived quality of services (QUALITY), and patient satisfaction (PTSAT) are the endogenous variables in this model. Arrows in the model specify our hypotheses about which variables are causing other latent variables. An endogenous variable may also influence another endogenous variable in the model. The relationship between patient expectations and perceived quality of services is a causal relationship between two endogenous variables.

Matrices

The intent of this article is to serve as a primer rather than a mathematical treatise, so the mathematical process for arriving at the structural equations is not discussed. The reader interested in understanding the calculations derived from matrix algebra is referred elsewhere.[1,12,13] Older versions of commonly used statistical packages for structural equation modeling like Lisrel[14] required an understanding of matrix algebra and Greek notation, but such knowledge is no longer essential. There is now a command language developed by the authors of Lisrel called SIMPLIS[15] that is more user friendly. Other programs, such as EQS,[16] were marketed originally without the need for knowledge of Greek notation. One only needs to know the name of the variables to test relationships. However, a cursory review of the literature and the Internet site devoted to structural equation modeling (SEMNET) demonstrates that quite a few researchers still refer to the matrices by their Greek notation.

The Structural Model

The structural equation for the latent variables involves the relationships among the concepts. Specifically, these relationships include the (1) relationships between the exogenous and endogenous factors (e.g., DEMO → EXPECT) and (2) relationships between the endogenous factors (e.g., EXPECT → QUALITY). An error variable is associated with each of the endogenous concepts and represents the latent error in the equation. The latent error, analogous to the residual term in regression, takes into account that there is usually some measurement error involved in the development and testing of a model. This error is represented in the model by the lone arrow leading to the endogenous variables (e.g., QUALITY).

The Measurement Model

Besides the structural (latent variable) model, one calculates a *measurement model*. As Figure 1 illustrates, the latent variables, even though conceptual in nature, are operationalized by what can be termed *observed variables, manifest variables, measures, proxies,* or *indicators.*[12] These indicators are variables that actually measure the construct. For instance, the exogenous factor "care received" is measured by three items: (1) information communicated by nurses (info), (2) availability of the caregiver (avail), and (3) nurse took time to listen (listen). The causal model can be tested with indicators that are single items, as in this case, or with scale scores derived from multiple items (e.g., a 10-item job satisfaction scale). What is crucial is that the items display sufficient reliability and validity. Structural equation modeling statistical packages (e.g., Lisrel) can be used to assess the construct validity of the indicators.[17]

Construct validity is evident when either *convergent validity* or *discriminant validity* are evident.

Evidence of convergent validity exists when there is overlap (i.e., correlation) of items on two measures of the same construct (e.g., two separate intelligence tests). Discriminant validity is evident when two tests that measure separate constructs are poorly correlated (e.g., a scale measuring job satisfaction should have a relatively low correlation with another scale measuring anxiety). Thus, the measurement model is used to demonstrate the relationship between the measured indicators and the conceptual latent variable. In the measurement model example, the relationships between the endogenous factors (e.g., patient expectations, perceived quality of services, and patient satisfaction) and their indicators (e.g., priexp, ovrqua, useagn) are shown.

As depicted in the model, each of the indicators has a lone arrow leading toward it. These arrows represent the error associated with the latent variable–indicator relationship. Such errors may be due to measurement flaws (e.g., imperfect reliability), inappropriate specification of the concept–indicator (or concept–concept) relationship, or omission of relevant variables in the overall model. Omissions frequently arise during the course of model development. Given the complexity of human behavior, it is an insurmountable task to arrive at a truly comprehensive model that considers all possible behaviors or variables. But leaving out a variable that is potentially a common cause of two other factors may result in spurious findings. An error such as this is a common violation of the underlying mathematical assumption that errors are not correlated.

Procedure

Once the investigator has sufficiently prepared a model, chosen valid and reliable indicators, and gathered data, he or she is prepared to test the model. The model is tested by estimating the coefficients and testing the goodness of fit of the hypothesized model to the data. Estimation is a product of the hypothesized relationships. For instance, in the example, care received is thought to have both a direct effect and an indirect effect (mediated by perceived quality of services) on patient satisfaction. Patient expectations (EXPECT) are also hypothesized to have an effect on patient satisfaction as mediated by perceived quality of services. The argument could be made that patient expectations may also have a direct effect on patient satisfaction.

Even though theory, common sense, and especially parsimony should drive the development of the model, statistical programs afford the opportunity to test variations of the model in an effort to arrive at the one that fits best. Best fit is arrived at by estimating the fit of the hypothesized model to the actual data. Model fit is tested by a likelihood-ratio chi-square statistic (χ^2).

When developing the model and testing its fit to the data, the advantages of causal modeling over other traditional techniques (e.g., regression analysis) become apparent: (1) solutions for models with multiple indicators can be generated, (2) latent variables can be introduced, (3) estimates of errors of measurement can be entered into the model (e.g., a scale with a reliability coefficient $\alpha = .83$ has an error of .17 that can be entered into the model), and (4) bidirectionality can be assessed (quality causing expectations *and* expectations causing quality).[18] A distinct advantage of causal modeling is its ability to simultaneously analyze all the factors pertinent to the model (in contrast, path analysis needs to be conducted in a step-by-step, linear fashion).

The data analyzed using structural equation modeling is usually composed of covariance or correlation matrices. (For a discussion of the use of correlations when using covariance structure modeling, see Cudeck[19]). In this example, the correlation coefficient was used as the unit of analysis, even though there are some experts who argue that covariances are more appropriate given that (1) the measured construct is maintained in its original metric and (2) correlations may result in imprecise estimates of the population variances and covariances.[12] However, the use of actual and fictitious data in this article made it problematic to derive comparable covariances. Table 1 provides the correlation matrix that was analyzed and also the syntax used for SIMPLIS (i.e., analysis with Lisrel).

Description of Syntax

The SIMPLIS language allows the researcher the option of using the actual variable name when writing the statistical commands rather than requiring familiarity with Greek notation. This convenience makes structural equation modeling more intelligible

Table 1

SYNTAX AND CORRELATION MATRIX FOR PATIENT SATISFACTION DATA

Observed Variables 'age' 'income' 'hlthprof' 'priorexp' 'exptx' 'expout' 'info' 'avail' 'listen' 'overqual' 'percacc' 'perctime' 'oversat' 'useagain' 'recommen'
correlation matrix

1.0														
.42	1.0													
.33	.52	1.0												
.27	.22	.27	1.0											
.35	.17	.22	.37	1.0										
.29	.07	.14	.42	.48	1.0									
.23	.22	.07	.23	.23	.19	1.0								
.26	.13	.12	.22	.17	.08	.51	1.0							
.25	.16	.22	.18	.19	.22	.44	.50	1.0						
.35	.18	.13	.14	.21	.21	.25	.29	.32	1.0					
.34	.21	.12	.18	.22	.17	.27	.32	.28	.52	1.0				
.33	.23	.22	.13	.17	.16	.26	.33	.29	.62	.65	1.0			
.28	.14	.21	.24	.21	.22	.51	.33	.63	.44	.43	.33	1.0		
.27	.16	.23	.26	.22	.23	.33	.20	.36	.37	.38	.35	.45	1.0	
.26	.18	.24	.29	.18	.22	.33	.33	.52	.35	.32	.36	.58	.65	1.0

Note: Sample size = 200.
Latent Variables 'DEMO' 'EXPECT' 'CARE' 'QUALITY' 'PTSAT'
Relationships
'age'=1*'DEMO'
'income'-'hlthprof'='DEMO'
'priorexp'=1*'EXPECT'
'exptx'-'expout'='EXPECT'
'info'=1*'CARE'
'avail'-'listen'='CARE'
'overqual'=1*'QUALITY'
'percacc'-'perctime'='QUALITY'
'oversat'=1*'PTSAT'
'useagain'-'recommen'='PTSAT'
'EXPECT'='DEMO' 'CARE'
'QUALITY'='EXPECT' 'CARE'
'PTSAT'='QUALITY' 'CARE'
Path Diagram
End of problem

to the new user. However, a fundamental understanding of matrix algebra can be especially fruitful when error messages arise, some of which border on the arcane. Alternatively, texts by Hayduk[1] and Bollen[12] may help the new user understand various error messages.

The "observed variables" mentioned in the first line of the command structure (Table 1) are the "indicator variables." Recall that indicator variables are those items or scales actually measured and attributed to the latent variables. A "correlation matrix" is identified as the mathematical unit of analysis. The correlation matrix is then entered into the program triangularly with a designated sample size of 200 to be analyzed. The "latent variables" are the hypothetical constructs. The "relationships" are the linkages between (1) the indicator variables and the latent variables (e.g., income – hlthprof = DEMO) and (2) the relationships between the latent variables (e.g., EXPECT = DEMO CARE). The reader will notice that for each latent variable one of the indicator variables is multiplied by 1 (e.g., age = 1* DEMO). This notation serves to assign a unit of measurement for each latent variable, thus standardizing the measurement process. That is, the unit of measurement in each latent variable equals its population standard deviation. For more information on the SIMPLIS language, see Joreskog and Sorbom.[15] Finally, "path diagram" is entered in the syntax; this recent addition to the Lisrel program provides the user with visual illustrations of the structural model, measurement model, *t*-values, and modification indices (to be discussed).

Once the syntax is established, the data can be analyzed to assess how well the model fits the data. It is important to emphasize that model development is based on theory, prior research, and observation and carries with it inevitable measurement or specification error. Furthermore, even if an adequate fit of the model is achieved, there may be alternate models or relationships. As Anderson and Gerbing[20] point out, models are never confirmed by data; they are supported or fail to be disconfirmed. Although a given model may fit the data well, other acceptable models may exist.

Generally, a two-step process of analysis is recommended. First the measurement model is tested and then the structural model is tested. Testing of the measurement model involves determining the fit of the indicators with the latent conceptual variables. No relationships between the latent variables are identified at this time. Testing of the structural model involves determining how well the entire model fits the data, including the relationships between the latent variables. It is interesting to note that when testing the measurement model (both for the exogenous and endogenous latent variables), one may actually be performing a confirmatory factor analysis. For example, we have hypothesized that age, income, and health profile best describe the latent variable demographics (DEMO). We can then test this a priori relationship by conducting a confirmatory factor analysis and thereby determine the fit of the indicators to the latent variable. Confirmatory factor analysis is a crucial step in that it establishes the psychometric properties (i.e., reliability and validity) of the constructs.

Models are never confirmed by data; they are supported or fail to be discomfirmed. Although a given model may fit the data well, other acceptable models may exist.

Initially, a confirmatory factor analysis was conducted to assess the strength of the measurement model (i.e., relationship between the latent variables and their indicators). Separate estimates were made of the (1) exogenous factors (DEMO and CARE) and their measures and (2) endogenous factors (EXPECT, QUALITY, and PTSAT) and their respective indicators. For the exogenous factors, R^2 was determined for each of the indicators. This statistic indicates the strength of the relationship between the latent variable and the specific scale or item. "Income" had the largest relationship with the demographics construct ($R^2 = .60$) whereas "availability of caregiver" had the largest relationship with the "care received" construct ($R^2 = .55$). All of the indicators had significant *t*-values (.05 level of significance), indicating that each of the indicator variables was a significant estimate of its respective latent variable. For the endogenous latent variables, expectation of outcome (expout) had the largest relationship with patient expectations (EXPECT) ($R^2 = .51$), perception of timeliness of services (perctime) had the largest relationship with perceived quality of services (QUALITY) ($R^2 = .71$), and likelihood of recommending services (recommen) had the largest relationship with patient satisfaction (PTSAT) ($R^2 = .71$). All of the indicators had significant *t*-values (.05 level of significance).

Results

Figure 2 provides the results of the Lisrel (parameter) estimates for the full model. These results are similar to regression coefficients. The significance of each parameter estimate is then tested using a *t*-test. Parameter estimates include estimates of the relationships between the latent variables and the indicator variables and the relationships between the various latent variables.

Goodness of Fit

Final analysis of the model involves determining how well the model fits the data. Does the model depicting patient satisfaction adequately fit the sample data? Part of the answer lies in the chi-square statistic (χ^2). This nonparametric statistic (normal distribution is not assumed) is employed to assess "goodness of fit." As opposed to convention, in this application a *nonsignificant* result (i.e., $p > .05$) is desired. One

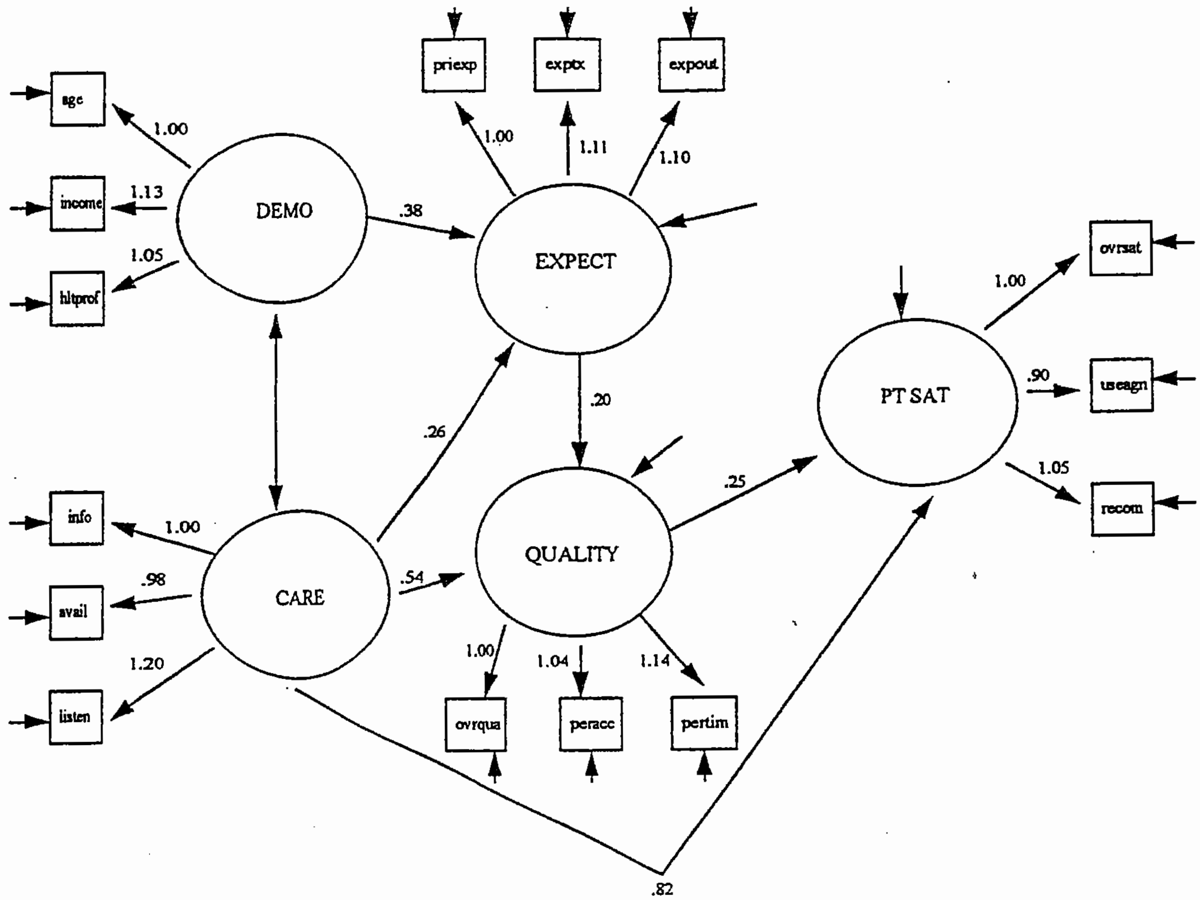

Figure 2. Patient satisfaction model with parameter estimates.

hopes that the hypothesized model does not drastically differ from the actual data. This statistic is fitted for each of the measurement models as well as the full conceptual model (i.e., all latent variables, exogenous and endogenous, and their indicators).

The chi-square was significant (p = .018) for the exogenous factors (the measurement model for DEMO and CARE), indicating that the model for these factors differed significantly from the data. However, chi-square statistics are notoriously sensitive to differences when sample sizes are large (approximately 200 and more). Thus, it is not unusual to scan the literature and find significant differences between the model and the data and yet have a desirable *fit.* This discrepancy occurs when the goodness-of-fit measures are calculated.

The Lisrel printout supplies an abundance of fit measures; the choice of which to use is contingent on sample size, change in number of parameter estimates, and whether the researcher is comparing alternative or nested models. The one most frequently cited is the goodness of fit index (GFI). Even though there is not broad consensus as to what exactly determines a good fit, generally if the index is at or above .90 an acceptable fit of the model to the data has been achieved. For the measurement model of the exogenous factors, the GFI was .97. This result suggests a good fit of the model to the data in spite of the fact that the chi-square statistic was significant. The chi-square was also significant (p = .026) for the endogenous factors, but the GFI was .96. It appears that the latent constructs are adequately measured by their indicators.

Modification to the Model

The Lisrel printout also provides *modification indices.* If there were problems with the measurement

Table 2

LIST OF LATENT AND OBSERVED VARIABLES.

Latent Variable	Observed Variable
DEMO (demographics)	age
	income
	hlthprof (health profile)
CARE (care received)	info (information communicated by nurse)
	avail (availability of caregiver)
	listen (nurse took time to listen)
EXPECT (patient expectations)	priorexp (overall expectation)
	exptx (expectations based on prior treatment)
	expout (expectation of outcome)
QUALITY (perceived quality of services)	overqual (overall perception of quality)
	percacc (perception of accuracy/ effectiveness)
	perctime (perception of timeliness of services)
PTSAT (patient satisfaction)	oversat (overall satisfaction with experience)
	useagain (likelihood would use services again)
	recommen (likelihood would recommend services)

model, for instance, and the item measuring health profile (hlthprof) was found to be more highly correlated with the conceptual variable care received (CARE) than its hypothesized construct demographics (DEMO), then the modification index will indicate this. The modification indices provide an estimate of the decrease in chi-square (keeping in mind that a low chi-square is desired as nonsignificance is sought) that would be achieved if you estimate the new relationship: CARE → hlthprofile. However, it is crucial to keep in mind that any modification made to the model must make theoretical and intuitive sense and not be based simply on the statistical output. It does not make sense to arbitrarily modify the model to achieve a decrease in chi-square if the change evolves into a nonsensical morass. Any change in the model, especially if it is data driven, must make sense.

Subsequently, the full structural equation model is tested. For the hypothesized sample model, all of the estimates were significant, with the exception of the path leading from EXPECT to QUALITY (estimate = .20, $t = 1.58$). This finding implies that the hypothesized model needs to be reconsidered, at least the EXPECT–QUALITY relationship needs further thought. As one wants to modify the model based on theory and prior empirical data, such a suggestion may require a literature search or discussions with colleagues.

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The objective of this article was to provide a brief summary of causal modeling and its potential application to patient satisfaction data. The increased popularity of structural equation modeling is indicated by the recent increase in publications based on the technique. But experts caution about the potential abuse associated with this statistical tool.[21] The wholesale employment of modeling applications like causal modeling may be problematic when researchers violate requirements like adequacy of measures, knowledge of structural relations, or theoretically driven models for testing.[21]

Computer software that is easy to use, like SIMPLIS, allows even the unsophisticated user to test models. Just because the technique is new and enticing should not lead researchers to use it when a technique like regression analysis would be sufficient, however. Ultimately, it should be the design and methodology (e.g., data collection, sampling, etc.) that drives the choice of analytic technique. When appropriate, modeling applications make a significant contribution to investigators interested in understanding multifactorial, interweaving, bidirectional relationships. Health care is rife with such relationships, and thus causal modeling would seem likely to be a powerful tool for exploring phenomena such as patient satisfaction with health care.

REFERENCES

1. Hayduk, L.A. *Structural Equation Modeling with LISREL.* Baltimore, Md.: Johns Hopkins University Press, 1987.
2. Cohen, J., and Cohen, P. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences.* 2nd ed. Hillsdale, N.J.: Erlbaum, 1983.
3. Pedhazur, E.J. *Multiple Regression in Behavioral Research.* 2nd ed. Fort Worth, Tex.: Holt, Rinehart, and Winston, 1982.
4. Fiore, J., Becker, J., and Coppel, D.B. "Social Network Interactions: A Buffer or a Stress?" *American Journal of Community Psychology* 11 (1983): 423–39.

5. Riggs, M.L., and Knight, P.A. "The Impact of Perceived Group Success-Failure on Motivational Beliefs and Attitudes: A Causal Model." *Journal of Applied Psychology* 79 (1994): 755–66.
6. Gotlieb, J.B., Grewal, D., and Brown, S.W. "Consumer Satisfaction and Perceived Quality: Complementary or Divergent Constructs?" *Journal of Applied Psychology* 79 (1994): 875–85.
7. Jackson, S.E. "Participation in Decision Making as a Strategy for Reducing Job-related Strain." *Journal of Applied Psychology* 68 (1983): 3–19.
8. Birnbaum, D., and Somers, M.J. "Fitting Job Performance into Turnover Model: An Examination of the Form of the Job Performance–Turnover Relationship and a Path Model." *Journal of Management* 19, no. 1 (1993): 1–11.
9. Revicki, D.A., Whitley, T.W., and Gallery, M.E. "Organizational Characteristics, Perceived Work Stress, and Depression in Emergency Medicine Residents." *Behavioral Medicine* 19 (1993): 74–81.
10. James, L.R., Mulaik, S.A., and Brett, J.M. *Causal Analysis: Assumptions, Models, and Data*. Beverly Hills, Calif.: Sage Publications, 1983.
11. Mulaik, S.A. "Toward a Conception of Causality Applicable to Experimentation and Causal Modeling." *Child Development* 58 (1987): 18–32.
12. Bollen, K. A. *Structural Equations with Latent Variables*. New York, N.Y.: Wiley, 1989.
13. Stevens, J. *Applied Multivariate Statistics for the Social Sciences*. 2nd ed. Hillsdale, N.J.: Erlbaum, 1992.
14. Joreskog, K.G., and Sorbom, D. *Lisrel 8 User's Reference Guide*. Chicago, Ill.: Scientific Software International, 1993.
15. Joreskog, K.G., and Sorbom, D. *Lisrel 8: Structural Equation Modeling with the SIMPLIS Command Language*. Chicago, Ill.: Scientific Software International, 1993.
16. Bentler, P.M. *EQS: Structural Equations Program Manual*. Los Angeles, Calif.: BMDP, 1989.
17. Widaman, K.F. "Hierarchically Nested Covariance Structure Models for Multitrait-Multimethod Data." *Applied Psychological Measurement* 9, no. 1 (1985): 1–26.
18. Biddle, B.J., and Marlin, M.M. "Causality, Confirmation, Credulity, and Structural Equation Modeling." *Child Development* 58 (1987): 4–17.
19. Cudeck, R. "Analysis of Correlation Matrices Using Covariance Structure Models." *Psychological Bulletin* 105, no. 1 (1989): 317–27.
20. Anderson, J.C., and Gerbing, D.W. "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach." *Psychological Bulletin* 103, no. 3 (1988): 411–423.
21. Brannick, M.T. "Critical Comments on Applying Covariance Structure Modeling." *Journal of Organizational Behavior* 16 (1995): 201–13.