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STRUCTURAL EQUATION MODELING
FOR TRAVEL BEHAVIOR RESEARCH

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Abstract

Structural equation modeling (SEM) is an extremely flexible linear-in-parameters multivariate statistical modeling technique. It has been used in modeling travel behavior and values since about 1980, and its use is rapidly accelerating, partially due to the availability of improved software. The number of published studies, now known to be more than fifty, has approximately doubled in the past three years. This review of SEM is intended to provide an introduction to the field for those who have not used the method, and a compendium of applications for those who wish to compare experiences and avoid the pitfall of reinventing previous research.

1. INTRODUCTION

Structural equation modeling (SEM) is a modeling technique that can handle a large number of endogenous and exogenous variables, as well as latent (unobserved) variables specified as linear combinations (weighted averages) of the observed variables.   Regression, simultaneous equations (with and without error-term correlations), path analysis, and variations of factor analysis and canonical correlation analysis are all special cases of SEM. It is a confirmatory, rather than exploratory method, because the modeler is required to construct a model in terms of a system of unidirectional effects of one variable on another. Each direct effect corresponds to an arrow in a path (flow) diagram. In SEM one can also separate errors in measurement from errors in equations, and one can correlate error terms within all types of errors.

Estimation of SEM is performed using the covariance analysis method (method of moments). There are covariance analysis methods that can provide accurate estimates for limited endogenous variables, such as dichotomous, ordinal, censored and truncated variables.   Goodness-of-fit tests are used to determine if a model specified by the researcher is consistent with the pattern of variance-covariances in the data. Alternative SEM specifications are typically tested against one another, and several criteria are available that allow the modeler to determine an optimal model out of a set of competing models.

SEM is a relatively new method, having its roots in the 1970s. Most applications have been in psychology, sociology, the biological sciences, educational research, political science, and market research. Applications in travel behavior research date from 1980. Use of SEM is now rapidly expanding as user-friendly software becomes available, and researchers become comfortable with SEM and regard it as another tool in their arsenal.

The remainder of this paper is divided into two main parts: an introduction to SEM, and a review of applications of SEM in travel behavior research.   Citations in the applications section are limited to models of travel behavior and values. Applications involving transportation from the perspectives of urban modeling, land use, regional science, geography, or urban economics are not included, unless such applications specifically include models of travel behavior or values.

2. METHODOLOGY

2.1. SEM Resources

SEM is firmly established as an analytical tool, leading to hundreds of published applications per year. Textbooks on SEM include Bollen (1989), Byrne (2001), Hayduk

(1987), Hoyle (1995), Kaplan (2000), Kline (1998), Loehlin (1998), Maruyama (1998), Mueller (1996), Schoenberg (1989), and Shipley (2000). Overviews of the state of the method can be found in and Cudeck, du Toit and Sörbom (2001), Jöreskog (1990), Mueller (1997), and Yuan and Bentler (1997). The multidisciplinary journal, *Structural Equation Modeling,* has been published quarterly since 1994. Available SEM software is listed in the Appendix.

2.2. The Defining Features of SEM

An SEM with latent variables is composed of up to three sets of simultaneous equations, estimated concurrently: (1) a measurement model (or submodel) for the endogenous (dependent) variables, (2) a measurement (sub)model for the exogenous (independent) variables, and (3) a structural (sub)model, all of which are estimated simultaneously. This full model is seldom applied in practice. Generally, one or both of the measurement models are dropped.   SEM with a measurement model and a structural model is known as SEM with latent variables. Alternatively, one can have structural model without any measurement models (SEM with observed variables), or a measurement model alone (confirmatory factor analysis). In general, an SEM can have any number of endogenous and exogenous variables.

An SEM structural model is used to capture the causal influences (regression effects) of the exogenous variables on the endogenous variables and the causal influences of endogenous variables upon one another. The structural model also allows specification of error-term covariances.   If the SEM also has a measurement model for the endogenous variables, the structural model involves latent endogenous variables rather than observed endogenous variables. Similarly, the SEM can have a measurement model and latent variables for exogenous variables. Simultaneous equations (typically estimated using instrumental variables methods) and path analysis are special cases of SEM with observed variables, while ordinary linear regression is the special case of SEM with one observed endogenous variable and multiple observed exogenous variables.

An SEM measurement model is used to specify latent (unobserved) variables as linear functions (weighted averages) of other variables in the system. When these other variables are observed, they take on the role of "indicators" of the latent constructs.[1] In this way, SEM measurement models are similar to factor analysis, but there is a basic difference. In exploratory factor analysis, such as principal components analysis, all elements of the matrix defining the latent variables (factors) in terms of linear combinations of the observed variables take on non-zero values. These values (factor

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[1] In advanced applications, models can be specified in which latent variables are functions only of other latent variables. Such "phantom" latent variables allow the modeler to constrain parameters to be within certain ranges (e.g., greater than zero) and to construct other types of special effects, such as random effects and period-specific effects in dynamic data.

loadings) generally measure the correlations between the factors and the observed variables, and rotations are routinely performed to aid in interpreting the factors by maximizing the number of loadings with high and low absolute values. In SEM, the modeler decides in advance which of the parameters defining the factors are restricted to be zero, and which are freely estimated or constrained to be equal to each other or to some non-zero constant. Also, in SEM one can also specify non-zero covariances among the unexplained portions of both the observed and latent variables. Specification of each parameter allows the modeler to conduct a rigorous series of hypothesis tests regarding the factor structure. Since there can be a large number of possible combinations in a measurement model with more than just a few variables, exploratory factor analysis is sometimes used to guide construction of an SEM measurement model.

An important distinction in SEM is that between direct effects and total effects. Direct effects are the links between a productive variable and the variable that is the target of the effect. Each direct effect corresponds to an arrow in a path (flow) diagram. An SEM is specified by defining which direct effects are present and which are absent. With most modern SEM software this can be done graphically by manipulating path diagrams. These direct effects embody the causal modeling aspect of SEM.[2] Total effects are defined to be the sum of direct effects and indirect effects, where the indirect effects represent the sum of all of the effects along the paths between the two variables that involve intervening variables. The total effects of the exogenous variables on the endogenous variables are sometimes known as the coefficients of the reduced-form equations.

The general SEM system is estimated using covariance (structure) analysis, whereby model parameters are determined such that the variances and covariances of the variables implied by model system are as close as possible to the observed variances and covariances of the sample. In other words, the estimated parameters are those that make the variance-covariance matrix predicted by the model as similar as possible to the observed variance-covariance matrix, while respecting the constraints of the model. Covariance analysis appears at first to be quite different from least square regression methods, but it can be viewed as an extension of least squares into the realm of latent variables, error-term covariances, and non-recursive models (i.e., models with feedback loops). In some simple cases, covariance analysis is identical to least squares. Estimation methodology is discussed in Section 2.5.

Advantages of SEM compared to most other linear-in-parameter statistical methods include the following capabilities: (1) treatment of both endogenous and exogenous variables as random variables with errors of measurement, (2) latent variables with multiple indicators, (3) separation of measurement errors from specification errors, (4) test of a model overall rather than coefficients individually, (5) modeling of mediating

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[2] For discussions of SEM in the context of causal modeling see Berkane (1997), Pearl (2000), Shipley (2000), and Sprites, Glymour and Scheines (2001).

variables, (6) modeling of error-term relationships, (7) testing of coefficients across multiple groups in a sample, (8) modeling of dynamic phenomena such as habit and inertia, (9) accounting for missing data, and (10) handling of non-normal data. These capabilities are demonstrated in many of the applications reviewed in Section 3.

2.3. A Brief History of Structural Equation Models

It is generally agreed that no one "invented" SEM. One simple view is that SEM is the union of latent variable (factor analytic) approaches, developed primarily in psychology and sociology, and simultaneous equation methods of econometrics. Upon closer inspection, we see that modern SEM evolved out of the combined efforts of many scholars pursuing several analytical lines of research. Bollen (1989) proposed that SEM is founded on three primary analytical developments: (1) path analysis, (2) latent variable modeling, and (3) general covariance estimation methods. Here we will highlight the contributions of each of these three areas.[3]

Path analysis, developed almost exclusively by geneticist Sewall Wright (1921)(1934), introduced three concepts: (1) the first covariance structure equations, (2) the path diagram or causal graph, and (3) decomposition of total effects between any two variables into total, direct and indirect effects. Shipley (2000) describes how and why path analysis was largely ignored in biology, psychology and sociology until the 1960s. Prior to the 1960s, econometricians also pursued the testing of alternative causal relationships through the use of overidentifying constraints on partial correlations (e.g., Haavelmo, 1943), but for many years economics was also uninformed about the solutions inherent in path analysis (Epstein, 1987; Shipley, 2000). During the 1960s and early 1970s, sociologists in particular (led by Blalock, 1961; Boudon, 1965; and Duncan, 1966) discovered the potential of path analysis and related partial correlation methods. Path analysis was then superseded by SEM, in which general covariance structure equations specify how alternative chains of effects between variables generate correlation patterns. Modern SEM still relies on path diagrams to express what the modeler postulates about the causal relationships that generate the correlations among variables.

The development of models in which inferences about latent variables could be derived from covariances among observed variables (indicators) was pursued in sociology during the 1960s. These latent variable models contributed significantly to the development of SEM by demonstrating how measurement errors (errors-in-variables) can be separated from specification errors (errors-in-equations). A seminal contribution was that of Blalock (1963). These models led directly to the first general SEM, developed by Jöreskog (1970)(1973), Keesling (1972) and Wiley (1973).

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[3] For more detailed perspectives on the genesis of SEM, see Aigner, *et al.* (1984), Duncan (1975), Goldberger (1972), Bielby and Hauser (1977) and Bentler (1980). Historical background is also discussed in many of the SEM texts listed in Section 2.1.

Wright's path analysis lacked the ability to test specific hypotheses regarding a postulated causal structure. Work by Lawley (1940), Anderson and Rubin (1956), and Jöreskog (1967)(1969) led to the development of maximum likelihood (ML) estimation methods for confirmatory factor analysis, which in tern led to the estimation of models in which confirmatory factor analysis was combined with path analysis (Jöreskog, 1970, 1973; Keesling 1972). ML estimation allowed testing of individual direct effects and error-term correlations, and it is still the most widely used estimation method for SEM (Section 2.5).

Modern SEM was originally known as the JKW (Jöreskog-Keesling-Wiley) model. SEM was initially popularized by the wide distribution of the LISREL (Linear Structural RELationships) program developed by Jöreskog (1970), Jöreskog, Gruvaeus and van Thillo (1970), and Jöreskog and Sörbom (1979).   For some time, SEM was synonymous with LISREL, but there are now many SEM programs available (see Appendix).

2.4. Model Specification and Identification

An SEM is constructed in terms of postulated direct effects between variables and optional error-term covariances of several types.   Each postulated effect usually corresponds to a free parameter.[4] If the SEM is has no measurement model(s) (no latent variables), there are four types of potential free parameters: (1) the (regression) effect of any exogenous variable on any endogenous variable, (2) the effect of any endogenous variable on any other endogenous variable (except itself), (3) variances of the unique portion (error term) of each endogenous variable, and (4) covariances between the error terms of any two endogenous variables. If the SEM contains latent endogenous variables, the above error-term variances and covariances pertain to error terms of latent endogenous variables, and the potential list of free parameters is increased to include: (5) the effect of a latent variable on its postulated observed-variable indicators (similar to factor loadings), and (6) variances of the unique portion (measurement error term) of each observed latent variable, and (7) covariances between the error terms of any two observed latent variables. If the SEM contains latent exogenous variables, there will be a similar opportunity for error-term variances and covariances pertaining to exogenous variables.   Modern SEM software allows specification of a model using one or more of three tools: matrix notation, symbolic equations, or graphically, by specifying arrows in a flow diagram.

We are usually in search of a parsimonious description of travel behavior. In SEM, the primary measure of parsimony is the *degrees of freedom* of the model, which equal to the difference between the number of free parameters in the model and the number of

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[4] Direct effects can also be set to fixed non-zero values, and free parameters can also be constrained to be equal to one another.

known quantities. The number of known quantities in covariance analysis is equal to the number of free elements in the variance-covariance matrix of the variables. The art of constructing an SEM is to specify an over-identified model in which only some of the possible parameters are free and many are restricted to zero, such that the model is nevertheless a reasonable representation of the phenomena under study (criteria for assessing model fit are the subject of Section 2.6). Theory and good sense must guide model specification. A saturated, or just-identified SEM, has zero degrees of freedom and fits perfectly, but it is only of interest as a baseline for certain goodness-of-fit criteria and as a means of exploring candidate parameters for restriction to zero. The most common ways of reducing model complexity are to eliminate weak regression effects, to reduce the number of indicators of each latent variable, and to minimize weak covariances between error terms. For SEM with latent variables, it is recommended that the measurement model(s) be developed first, followed by the structural model (Anderson and Gerbing, 1988).

Estimation of a model is not possible if more than one combination of parameter values will reproduce the same data (covariances). Such an indeterminate model is termed to be unidentified, or under-identified. In models of travel behavior with a single endogenous variable, identification is not generally a problem, except when caused by special patterns in the data (empirical under-identification). In SEM, empirical under-identification can also be a problem, but the cause of an indeterminate solution is usually the design of the model (structural under-identification). The flexibility of SEM makes it fairly easy to specify a model that is not identified.

Heuristics are available to guide the modeler. There are separate rules of thumb for the measurement model and structural model, but an entire system may be identified even if a rule of thumb indicates a problem with one of its submodels, because restrictions in one submodel can aid in identifying the other submodel. Rules of thumb for identification of measurement models are reviewed in Bollen (1989: 238-254), Reilly (1995) and Shipley (2000: 164-171). These rules involve the number of observed variables to which each latent variable is linked and whether or not the error terms of the latent variables are specified as being correlated.[5]

Rules of thumb for identification of structural models (and the only concern for SEM with observed variables) are reviewed in Bollen (1989: 88-104), Rigdon (1995) and Shipley (2000: 171-173). Basically, all recursive models, in which there are no feedback loops in the chains of direct effects, will be identified as long as there are no error-term correlations. Non-recursive models can be broken into blocks in which all feedbacks are contained within a block, so that the relationship between the blocks is recursive. If each block satisfies identification conditions, then the entire model is also identified

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[5] The "three measure rule" asserts that a measurement model will be identified if every latent variable is associated with at least three observed variables; and the "two measure rule" asserts that a measurement model will be identified if every latent variable is associated with at least two observed variables and the error term of every latent variable is correlated with at least one other latent variable error term.

(Fox, 1984; Rigdon, 1995). The modeler can also check the rank order of a composite matrix involving the exogenous variable effects and the effects among the endogenous variables to verify that a structural model will be identified even if there are unlimited error-term correlations (Bollen, 1989).

Confronted with an under-identified model, an SEM estimation program might diagnose the identification problem. However, detection is not guaranteed, and the program might either produce peculiar estimates or fail to converge to a solution. Detection is generally based on interrogating the rank of the information matrix of second-order derivatives of the fitting function. Unfortunately, rank is almost always evaluated sequentially and pertains only to a local solution. Thus, when a deficiency is detected, only the first parameter involved in the problem is identified and there is no information about other parameters that are also involved in the indeterminancy (McDonald, 1982). Identification problems can also be uncovered by testing whether the same solution is obtained when re-estimating the model with an alternative initial solution, or by substituting the model-reproduced variance-covariance matrix for the sample matrix. Also, by using methods of modern computer algebra, the rank of an augmented version of the Jacobian matrix of first derivatives of the fitting function can establish whether a model is structurally identified (Bekker, Merckens and Wansbeek (1994). Abnormally large standard errors and coefficient covariances are evidence of undetected identification problems.

2.5. Estimation Methods and Sample Size Requirements

The fundamental principle of covariance analysis is that every linear statistical model implies a variance-covariance matrix of its variables. The functional form of every element in the combined variance-covariance matrix of the endogenous and exogenous variables can be derived from the SEM equations using simple matrix algebra. Covariance analysis works by finding model parameters such that the variances and covariances implied by model system are as close as possible to the observed variances and covariances of the sample. In simple multiple regression, this exercise leads to the normal equations of ordinary least squares. For SEM with multiple endogenous variables, especially SEM with latent variables, estimation becomes more challenging, and quite a few different methods have been developed. Selection of an appropriate SEM estimation method depends on the assumptions one is willing to make about the probability distribution, the scale properties of the variables, the complexity of the SEM, and the sample size.

The mostly commonly used SEM estimation methods today are: normal-theory maximum likelihood (ML), generalized least squares (GLS), weighted least squares (WLS), in forms such as asymptotically distribution free weighted least squares (ADF or

ADF-WLS), and elliptical reweighted least squares (EGLS or ELS).[6] These methods all involve a scalar fitting function that is minimized using numerical methods. Parameter standard errors and correlations are computed from the matrices of first and second derivatives of the fitting function. The product of the optimized fitting function and the sample size is asymptotically chi-square distributed with degrees of freedom equal to the difference between the number of free elements in the observed variance-covariance and the number of free parameters in the model.[7] In SEM group models, the variance-covariance data are stacked and hypotheses tests can be conducted to determine the extent to which each group differs from every other group.

ML is the method used most often. The ML solution maximizes the probability that the observed covariances are drawn from a population that has its variance-covariances generated by the process implied by the model, assuming a multivariate normal distribution. The properties of ML estimators have been thoroughly investigated with respect to the effect of violations from normality and sample size on biases of estimators, nonconvergence, and improper solutions (e.g., Boomsma, 1982; Bollen, 1989; Finch, *et al.*, 1997; Hoogland and Boomsma, 1998; and Kline, 1998). The bottom line is that ML estimation is fairly robust against violations of multivariate normality for sample sizes commonly encountered in transportation research. Simulation studies have shown that excess kurtosis is the main cause of biases in standard errors and goodness-of-fit of ML estimates, and some software packages provide measures of multivariate kurtosis (Mardia, 1970) as an aid in assessing the accuracy of ML estimates and goodness of fit; skewness is less of a problem. Corrections have also been developed to adjust ML estimators to account for non-normality. These include a robust ML standard error estimator (RML) (Browne, 1984; Bentler, 1995) and a scaled ML test statistic (SML) (Satorra and Bentler, 1988). In addition, Bayesian full-information ML estimators based on the EM algorithm are now becoming available for use with missing and non-normal data (Lee and Tsang, 1999; Lee and Shi, 2000).

The robustness of ML estimation and the correction factors that have been developed for non-normal data mean that SEM with ML estimation can be used in many situations with discrete choice variables, with ordinal scales used to collect data on feelings and perceptions (e.g., Likert scales), and with truncated and censored variables.[8] However, in order to further minimize biases, ADF-WLS and related elliptical estimators for SEM

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[6] Lesser used methods include unweighted least squares (ULS), diagonally weighted least squares (DWLS), and instrumental variable (IV) methods, such as three-stage least squares. IV methods are sometimes used to establish initial values for ML, GLS and WLS.

[7] Depending on the estimation method and whether the correlation or variance-covariance matrix is being analyzed, either the sample size or the sample size minus one is used in the chi-square calculation. Also, under certain assumptions, the chi-square distribution can be considered to be non-central, and some goodness-of-fit criteria (Section 2.6) correspond to how well a model reduces the noncentrality parameter of the distribution.

[8] A current limitation is that SEM estimation methods will only support dichotomous and ordered polychotomous categorical variables. This means that a multinomial discrete choice variable must be represented in terms of a multivariate choice model by breaking it down into component dichotomous variables linked by free error covariances (Muthén, 1979).

have been specifically designed for limited endogenous variables. These estimators have been shown to be consistent and asymptotically efficient, with asymptotically correct measures of model goodness-of-fit, under a broad range of conditions (Bentler, 1983; Browne, 1982, 1984; Muthén, 1983, 1984; Bock and Gibbons, 1996). Comparisons of the performance of ADF-WLS versus alternative methods are provided by Sugawara and McCallum (1993), Fan, *et al.*, (1999) and Boomsma and Hoogland (2001). The major disadvantage of ADF-WLS and related estimators is that they require a larger sample size compared to ML, due to their heavy reliance on asymptotic assumptions and required computation and inversion of a matrix of fourth-order moments.[9]

Sample size issues have received considerable attention (e.g., Anderson and Gerbing, 1988; Bentler, 1990; Bentler and Yuan, 1999; Bollen, 1990; Hoogland and Boomsma, 1998). The consensus is that the minimum sample sizes for ADF-WLS estimation should be at least 1,000 (Hoogland and Boomsma, 1998), some say as high as 2,000 (Hoyle, 1995; Ullman, 1996; Boomsma and Hoogland, 2001). ML estimation also requires a sufficient sample size, particularly when non-normal data are involved. Based on Monte Carlo studies of the performance of various estimation methods, several heuristics for have been proposed: (1) A minimum sample size of 200 is needed to reduce biases to an acceptable level for any type of SEM estimation (Kline, 1998; Loehlin, 1998; Boomsma and Hoogland, 2001). (2) Sample size for ML estimation should be at least fifteen times the number of observed variables (Stevens, 1996). (3) Sample size for ML estimation should be at least five times the number of free parameters in the model, including error terms (Bentler and Chou, 1987; Bentler, 1995); and (4) with strongly kurtotic data, the minimum sample size should be ten times the number of free parameters (Hoogland and Boomsma, 1998). Bootstrapping is an alternative for ML estimation with small samples (Shipley, 2000).

2.6. *Assessing Goodness of Fit and Finding the Best Model*

Many criteria have been developed for assessing overall goodness of fit of an SEM and measuring how well one model does versus another model.[10] Most of these evaluation criteria are based on the chi-square statistic given by the product of the optimized fitting function and the sample size. The objective is to attain a *nonsignificant* model chi-square, since the statistic measures the difference between the observed variance-covariance matrix and the one reproduced by the model. The level of statistical significance indicates the probability that the differences between the two matrices are due to sampling variation. While it is generally important to attain a nonsignificant chi-square, most experts suggest that chi-square should be used as a measure of fit, not as

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[9] A previous disadvantage of WLS and related methods, computational intensity, has been eliminated with the capabilities of modern personal computers.

[10] For overviews of SEM goodness-of-fit, see Bentler (1990), Bollen and Long (1992), Gerbing and Anderson (1992), Hu and Bentler (1999), and Mulaik, *et al.* (1989).

a test statistic (Jöreskog and Sörbom, 1993). One rule of thumb for good fit is that the chi-square should be less than two times its degrees of freedom (Ullman, 1996).

There are problems associated with the use of fitting-function chi-square, mostly due to the influences of sample size and deviations from multinormality. For large samples it may be very difficult to find a model that cannot be rejected due to the direct influence of sample size. For such large samples, Critical N (Hoetler, 1983) gives the sample size for which the chi-square value would correspond to p=.05; a rule of thumb is that critical N should be greater than 200 for an acceptable model (Tanaka, 1987). For small sample sizes, asymptotic assumptions become tenuous, and the chi-square value derived from the ML fitting function is particularly sensitive to violations from multinormality. Many of the following goodness-of-fit indices use normalizations to cancel out sample size in the chi-square functions, but the mean of the sampling distribution of these indices is still generally a function of sample size (Bollen, 1990, Bentler and Yuan, 1999).

Goodness-of-fit measures for a single model based on chi-square values include: (1) root mean square error of approximation (RMSEA) which measures the discrepancy per degree of freedom (Steiger and Lind, 1980), (2) Z-test (McArdle, 1988), and (3) expected cross validation index ECVI (Browne and Cudeck, 1992). Most SEM programs provide these measures together with their confidence intervals. It is generally accepted that the value of RMSEA for a good model should be less than 0.05 (Browne and Cudeck, 1992), but there are strong arguments that the entire 90% confidence interval for RMSEA should be less than 0.05 (MacCallum *et al.,* 1996).

Several goodness-of-fit indices compare a proposed model to an independence model by measuring the proportional reduction in some criterion related to chi-square; the indices.[11] Most programs calculate several of these indices using the definition of an independence (null) model with no restrictions whatsoever. Using such a baseline, a rule of thumb for most of the indices is that a good model should exhibit a value greater than 0.90 (Mulaik, *et al.,* 1989; Bentler, 1990; McDonald and Marsh, 1990). Unfortunately, in many applications these indices will be very close to unity because of the very large chi-square values associated with such independence models. This renders them of little use when distinguishing between two well-fitting models. However, there is more than one interpretation of an independence model, so these indices should be recalculated using a baseline model that is appropriate for each specific application (Sobel and Bohrnstedt, 1985).

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[11] These indices, which mainly differ in terms of the normalization used to account for sample size and model parsimony, include: (1) normed fit index, which is variously designated in SEM software output as NFI, BBI, or Δ_1 (Bentler and Bonett, 1980); (2) non-normed fit index (NNFI, TLI or RNI) (Tucker and Lewis, 1973, Bentler and Bonett, 1980); (3) comparative fit index (CFI) (Bentler, 1989, Steiger,1989); (4) parsimonious normed fit index (PNFI) (James, Mulaik, and Brett, 1982); (5) relative normed index (designated as RFI or ρ) (Bollen, 1986); and (6) incremental fit index (IFI or Δ_2) (Bollen, 1989 and Mulaik, 1989).

The performance of models with substantially different numbers of parameters can be compared using criteria based on Bayesian Theory. The Akaike Bayesian Information Criterion (variously abbreviated as ABIC, BIC or AIC) compares ML estimation goodness of fit and the dimensionality (parsimony) of each model (Akaike, 1974, 1987).[12] Modifications of the ABIC, the Consistent Akaike Information Criterion, or CAIC (Bozdogen, 1987) and the Schwarz Bayesian criterion, or SBC (Schwarz, 1978), take into account the sample size as well as the model chi-square and number of free parameters. These criteria can be used not only to compare two alternative models of similar dimensionality, but also to compare how the models to the independence model at one extreme and the saturated model (perfect fit) at the other extreme. The model that yields the smallest value of each criterion is considered best.

Finally, goodness of fit measures based on the direct comparison of the sample and model-implied variance-covariance matrices include: (1) The root mean square residual (RMR, or average residual value), (2) the standardized RMR (SRMR), which ranges from zero to one, with values less than 0.05 being considered a good fit (Byrne, 2001; Steiger, 1990), (3) the goodness-of-fit index (GFI), (4) the adjusted goodness-of-fit index (AGFI, which adjusts GFI for the degrees of freedom in the model), and (5) the parsimony-adjusted goodness-of-fit index (PGFI) (Mulaik, *et al.,* 1989). R^2 values are also available by comparing estimated error-term variances to observed variances. It is important to distinguish between R^2 values for reduced form equations and those for the structural equations.

Based on these goodness-of-fit tests for a model, a travel demand modeler can take one of three different courses of action: (1) Confirm or reject the model being tested based on the results. If a model is accepted, it should be recognized that other unexamined models might fit the data as well or better. Confirmation only means that a model is *not rejected*. (2) Two or more competing models can be tested against each other to determine which has the best fit. The candidate models would presumably be based on different theories or behavioral assumptions. (3) The modeler can also develop alternative models based on changes suggested by test results and diagnostics, such as first-order derivatives of the fitting function. Models confirmed in this manner are post-hoc. They may not fit new data, having been created based on the uniqueness of an initial dataset. The availability of published results from previous studies affects the balance between a confirmatory or exploratory approach for a given application. Such results from structural equation modeling in travel behavior research are reviewed in the remainder of this paper.

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[12] Discussions of the role of parsimony in model evaluation and the effects of sample size and model complexity on criteria such as the three used here are provided by Bentler (1990), Bentler and Bonett (1980), McDonald and Marsh (1990), and Mulaik, *et al.* (1989).

3. TRAVEL BEHAVIOR APPLICATIONS

The earliest known applications of SEM to travel behavior are a joint model of vehicle ownership and usage (Den Boon, 1980, reviewed in Section 3.1) and a dynamic model of mode choice and attitudes (Lyon, 1981a and 1981b, Section 3.2). Tardiff (1976) and Dobson, *et al.* (1978) (Section 3.4) developed simultaneous equation models of travel behavior and attitudes that are precursors to full-blown SEM applications, and insightful early discussions of SEM as a potential tool in modeling travel demand are to be found in CRA (1978) and Allaman, *et al.* (1982). The following bibliography is organized by topic, and the citations within each section are generally in chronological order.

3.1. *Travel Demand Modeling Using Cross-sectional Data*

Models of vehicle ownership and usage are a natural application for SEM, through which it is possible to capture the mutual causal effects between vehicle ownership and distance traveled in a simultaneously estimated system, rather than through sequential estimation with selectivity corrections. Den Boon (1980) shows how this can be accomplished. Later, Golob (1998) modeled travel time, vehicle miles of travel and car ownership together, using data for Portland, Oregon. A model of household vehicle usage and driver allocation was developed by Golob, Kim and Ren (1996). WLS estimation is used with U.S. data for urban regions within California. Vehicle usage is expressed in reduced-form equations as a function of household and vehicle characteristics.

Pendyala (1998) investigates the dependence of SEM on the homogeneity of a causal travel behavior process across the population of interest. Results are presented from models estimated on simulated data generated from competing causal structures. These estimates are shown to perform poorly in the presence of structural heterogeneity.

Fujii and Kitamura (2000) and Golob (2000) developed models of trip chain generation. As these models encompass activity duration in addition to conventional travel measures of trip generation and travel time, they are further discussed in Section 3.3.

Axhausen, *et al.* (2001) tests causal hypotheses linking car ownership, season ticket ownership and modal usage in Switzerland. The results confirm the dominance of car ownership, which drives the other variables. However, car usage was found to be complementary with public transport usage through direct positive links to season ticket ownership and public transport usage. Following up on this work, Simma and Axhausen (2001a) compared interrelationships between car ownership, season tickets, and travel and found consistent results in models using similar data from three countries (Germany, Great Britain, and Switzerland).

Simma and Axhausen (2001b) demonstrate an SEM that captures relationships between male and female heads of household with regard to travel demands. The endogenous variables were car ownership, distances traveled by males and females, and male and female trips by two types of activities. Exogenous variables included the employment status of each head, family characteristics, and measures of residential accessibility and local land use.

Finally, Simma (2000) and Simma, *et al.* (2001) investigated the effects of spatial structure on car ownership, trips by mode and travel distance, using trip diary and environmental data for Austria. Household-based accessibility measures were found to be more influential than municipal and regional measures developed from gravity models and land use characteristics.

3.2. Dynamic Travel Demand Modeling

Panel data modeling is a natural application for SEM. Models can be specified with variables repeated variables joined by lagged causal effects and possibly autocorrelated error structures. Moreover, time-invariant individual-specific terms can be incorporated in error structures, and period effects can be isolated with certain types of panel data.

Lyon (1981a)(1981b)(1984) was the first to develop a dynamic SEM incorporating travel choices and attitudes. At the time of this work, the lack of available SEM estimation methods for non-normal variables motivated the use of a sequential IV approach to parameter estimation. This work represents an important breakthrough in the application of SEM to the modeling of travel behavior and values. SEM allows the exploration of mutual causality between attitudes and behavior (Section 3.4).

Golob and Meurs (1987)(1988) are early examples of SEM applied to (Dutch) panel trip diary data. These models suffer from a lack of exogenous variable effects. Golob and van Wissen (1989) unify explanation of car ownership and travel distances by mode, but the SEM is once again short on exogenous household characteristics, with the exception of household income. ML estimation is applied to Dutch data.

In joint dynamic models of car ownership and trip generation (Golob, 1989) and car ownership and travel time expenditures (Golob, 1990b) it is demonstrated that an SEM applied to (Dutch) panel data is able to capture both panel conditioning biases and period effects. The models also capture lags between car travel needs and vehicle transactions and incorporate autocorrelated errors. In a related discussion that is now outdated, Golob (1990a) explores use of SEM with panel data on travel choices.

Kitamura (1989) uses dynamic log-linear models (GLM) applied to Dutch panel survey data instead of SEM to test alternative causal postulates concerning travel behavior. In general, SEM and GLM are intimately related (McCullagh and Nelder, 1989), and Van

Wissen and Golob (1990) directly compare GLM and SEM on the same data. The authors conclude that SEM is more effective in distinguishing the performance of competing hypotheses.

Once again using panel data for the Netherlands, Van Wissen and Golob (1992) present a dynamic SEM of car fuel type choice and mobility that captured influences of reduced vehicle operating costs on latent demand for car travel. The model incorporates individual-specific, time-invariant effects. WLS estimation was used.

Using data from a two-wave panel survey of residents of Davis, California, Mokhtarian and Meenakshisundaram (1998)(1999) develop dynamic models of travel and three communication activities: personal meetings, object transfer (e.g., mail), and electronic transfer (phone, fax, and email). The authors found very little evidence of the substitution of electronic communication for trips. The relatively small sample size restricts model complexity. ML estimation was used.

Fujii and Kitamura (2000a) use multi-day panel data from drivers in the Osaka-Kobe Region of Japan to test hypotheses concerning how drivers collect and process information about anticipated travel time. Anticipated travel time is modeled as a function of lagged anticipated time, lagged actual time, and time forecasted by different sources (e.g., mass media and word-of-mouth). The relatively small sample size called for ML estimation.

Multi-day travel is also modeled by Simma and Axhausen (2001c). Using a six-week travel diary for areas in Germany and pooling the data by week, the authors present SEM results that shed light on the nature of linkages between travel on successive days of the week, for individuals and household couples, in terms of both travel distances and trip making.

3.3. Activity-Based Travel Demand Modeling

SEM has considerable potential here. Activity participation and travel can be modeled within a comprehensive framework that captures: (1) the direct relationships between activity demand and the need to travel to get to activity sites, (2) interrelationships between participation in different activities, and (3) feedbacks from travel time to activity time (travel time "budget effects"), all conditional on personal and household characteristics. Kitamura (1997) and Pas (1997a)(1997b) provide comprehensive overviews of activity-based travel demand modeling that include discussions of the role of SEM.

Kitamura, *et al.* (1992) and Golob, Kitamura and Lula (1994) were the first to apply SEM in modeling joint demand for activity duration and travel. Results, estimated using ML applied to California time-use survey data, confirm a negative feedback of commute

time to non-work activities; individuals with longer commutes have less time available for discretionary activities.

Lu and Pas (1999) present an SEM of in-home activities, out-of-home activities (by type), and travel (measured various ways), conditional on socioeconomic variables. Estimation is by ML, and the emphasis is on interpretation of the direct and indirect effects. The activity diary data are for the Greater Portland, Oregon Metropolitan Area.

Golob and McNally (1997) model the interactions of household heads in activity and travel demand. Activities are divided into three types, and SEM results are compared using ML and WLS estimation methods. The authors conclude that, where possible, WLS methods should be used to estimate SEM applied to activity participation data.

Gould and Golob (1997) and Gould, *et al.* (1998) use SEM to explore how travel time saved by working at home or shopping close to home might be converted to other activities and other travel. Certain population segments were found to exhibit latent demand for activities. ML estimation is applied to Portland data.

Golob (1998) develops a joint SEM of vehicle ownership, activity participation (by activity type), travel time expenditure (by trip purpose), and household aggregate vehicle miles of travel. The major distinction of this work is that an ordered discrete-choice household car ownership variable is included together with time-use and distance generation variables in a single SEM. WLS is used with data for Portland.

Two independent joint trip-chain and time use models were also published in 2000. Fujii and Kitamura (2000b) studied the latent demand effects of the opening of new freeways. The authors used an SEM to determine the effects of commute duration and scheduling variables on after-work discretionary activities and their trips. They used sequential instrumental variables estimation, which they refer to as a measurement model. Data are for the Osaka-Kobe Region of Japan. Similarly, Golob (2000) estimated a joint model of work and non-work activity duration, four types of trip chains, and three measures of travel time expenditure. ML estimation was applied to Portland data, and the effects of in-home work and residential accessibility were explored using the model.

Finally, Kuppam and Pendyala (2001) present three separate models estimated using WLS applied to data for Washington, DC. The models focussed relationships between: (1) activity duration and trip generation, (2) durations of in-home and out-of-home activities, and (3) activity frequency and trip chain generation.

3.4. Attitudes, Perceptions and Hypothetical Choices

Applied to data on attitudes, perceptions, stated behavioral intentions, and actual behavior, SEM can be used to specify and test alternative causal hypotheses. It has

been found that, as might be expected, causality is often mutual. The assumption that behavior is influenced by attitudes, perceptions, and behavioral intentions without feedbacks does not hold up when tested using SEM. These results challenge the assumption, held by some, that stated preference (SP) choices or ratings can be directly scaled into revealed-preference (RP) choice models. SEM results show that, in most applications, SP data are a direct function of RP choice.

Tardiff (1976) uses path analysis to demonstrate empirical evidence that the causal link from choice behavior to attitudes is stronger than the link from attitudes to choice behavior. Subsequent studies using different forms of simultaneous equation modeling showed consistently that attitudes, especially perceptions, are conditioned by choices, while at the same time, attitudes affect choices (e.g., Dobson, *et al.*, 1978).

Golob, Kitamura and Supernak (1997) develop models in which changes in travel times, attitudes toward carpooling, mode choice, and use of an exclusive freeway lane for carpools are modeling over time using panel survey data for San Diego, California. The SEM, which assumes ordinal scales and discrete choice variables, has individual-specific terms that take advantage of repeated measurements to account for population heterogeneity.

Golob and Hensher (1998) employ SEM to address the dichotomy between an individual's behavior and his or her support for policies that are promoted as benefiting the environment. Through the use of latent variables, attitudes are related to behavioral variables representing mode choice and choice of compressed work schedules, all of which are conditioned by a set of exogenous variables. The attitude scales are treated as ordinal, choices are treated as discrete, and the SEM is estimated using WLS applied to data for major Australian urban areas.

An SEM that combines SP and RP data from same households in California to explain vehicle usage as a function of vehicle type, vintage, fuel type to predict use of limited range electric vehicles is developed by Golob, Bunch and Brownstone (1997). Joint SP and RP estimation using SEM allows SP and RP error terms to be correlated while simultaneously testing for causal effects of RP (experiences) on SP (preferences).

Morikawa and Sasaki (1998) employ an SEM in concert with a discrete choice model to capture the influence of latent subjective indicators of the attributes of choice alternatives on choice. Using a Dutch survey of inter-city travel and joint ML estimation, the authors conclude that models with causality only from attitudes to behavior perform less well than those that incorporate a causal feedback to attitudes from behavior. The preferred model involves estimation of the SEM and discrete choice equations simultaneously.

Levine, *et al.* (1999) present two latent variable models that explain financial support for public transport and support for an institutional reform in public transit planning. The models, estimated using ML applied data collected in Southeast Michigan, contain as

many as six latent endogenous variables with observed ordinal and discrete indicators, and several sociodemographic variables.

An SEM with five latent variables is used by Jakobsson *et al.* (2000) to investigate causality among acceptance of road pricing, behavioral intention concerning reductions in car usage, and feelings related to fairness and infringement on personal freedom. ML is applied using data from a Swedish survey.

Stuart, *et al.* (2000) used SEM to determine how a series of ratings of attributes of the New York Subway (e.g., crowding, personal security, cleanliness, predictability of service) are related to customers' ratings of value and overall satisfaction with the system. ML estimation is applied using sample of over 1,000 transit panel participants.

In a combination of attitudinal and activity-based modeling, Fujii, Kitamura and Kishizawa (2000) used SP (budget allocation) and RP data collected in the Osaka-Kobe Region to estimate an SEM in a study joint activity engagement. Satisfaction with the activity pattern, discretionary trip frequency, and discretionary travel time are modeled as a function of in-home and out-of-home activity duration broken down by household activity participation. Sequential IV estimation is used.

Sakano and Benjamin (2000) developed an SEM that modeled SP responses concerning a new mode, together with attitudes and perceptions about the travel environment, and exogenous personal and modal characteristics. The data are for Winston-Salem and Greensboro, NC, and ML estimation is used. An important contribution is that model forecasts are computed and interpreted.

Gärling *et al.* (2001) explores decision making involving driving choices by using an SEM with latent variables to test links among attitude towards driving, frequency of choice of driving, and revealed presence of a certain type of decision process known as script-based. ML estimation is applied to Swedish survey data. The authors followed up the SEM results with laboratory experiments.

The effects of negative critical incidents on cumulative satisfaction with public transport is determined by Friman *et al.* (2001) by applying an SEM with a measurement model to Swedish data on attitudes and experiences. Friman and Gärling (2001) extend the results of the first study by applying an SEM to stated preference data involving satisfaction under a variety of conditions involving treatment by public transport employees, service reliability, clarity of service information, and comfort.

Golob (2001) tested a series of joint models of attitude and behavior to explain how both mode choice and attitudes regarding a combined HOV and Toll facility (HOT lanes) differ across the population. Applying WLS estimation to a dataset from San Diego California, the author demonstrates that choices appear to influence some opinions and perceptions, but other opinions and perceptions are independent of behavior and

dependent only on exogenous personal and household variables. None of the models tested found any significant effects of attitudes on choice.

Finally, Sakano and Benjamin (2001) estimate an SEM comprising: (1) endogenous RP choices, (2) endogenous SP choices, (3) endogenous attitudes, in the form of attribute importance ratings, (4) exogenous mode characteristics, and (5) exogenous personal characteristics. ML estimation was applied to data collected in the Puget Sound Region.

3.5. Organizational Behavior and Values

Golob and Regan (2000) applied SEM in the form of confirmatory factor analysis with regressor variables (estimated using WLS) to analyze the interrelationships among fleet managers' evaluations of twelve proposed congestion mitigation policies. The data are from a survey of managers of trucking companies operating in California,

Using these same data, Golob and Regan (2001a) used an SEM to determine how perceptions concerning five aspects of traffic congestion problem differ across sectors of the trucking industry. The model also simultaneously estimates how these five aspects combine to predict the perceived overall magnitude of the problem, and multi-group estimation is used to determine how results vary across industry sectors.

Finally, Golob and Regan (2001b) use SEM in the form of a multivariate probit model to captured the influences of each of twenty operational characteristics on the propensity of trucking company managers to adopt each of seven different traveler information technologies. The authors discuss using SEM with WLS estimation as an alternative to simulated moments for estimating multivariate probit models.

3.6. Driver Behavior

Driver behavior (or more generally, user behavior) is a growing subject area for the application of SEM. Traffic safety is one potential focus, while another is the application of advanced technologies such as vehicle navigation systems and advanced traveler information systems (ATIS).

Donovan, J.E. (1993) studied how driving under the influence of alcohol is related to other types of behavior using SEM. Using survey data collected in Colorado, the author concluded that problematic driving behaviors are related to more general lifestyle choices involving unconventional psychosocial behavior.

In a study of the behavior of long-distance truck drivers, Golob and Hensher (1996) tested alternative hypotheses concerning causal relations between drug taking, compliance with shipping schedules and the propensity to speed, using data from an

Australian survey and WLS estimation. The authors concluded that increasing speed is positively influenced by the propensity to take stay-awake pills, which is itself influenced by the propensity to self-impose schedules. McCartt, *et al.* (1999) present results from a similar application of SEM using data from a survey of long-distance truck drivers in New York State.

In a study of the user-interface of route guidance systems, Fujii, *et al.* (1998) modeled experimental data to determine how comprehension of map displays are related to the attributes of the display and sociodemographic characteristics of the driver.

Finally, Ng and Mannering (1999) used SEM to analyze experimental data from a driving simulator on drivers' speed behavior as a function of different types of advisory information (in-vehicle and out-of-vehicle). Speeds and speed variances were modeled using instrumental variables.

4. SUMMARY

Structural equation modeling is becoming widely used in travel behavior research, as witnessed by the more than fifty applications cited in this review. Half of these applications have been published within the past three years. SEM is certainly not appropriate for many applications, but it should be another tool in the arsenal of the well-prepared travel behavior researcher. A review of the literature cited here will hopefully aid researchers in determining appropriate usage.

ACKNOWLEDGEMENTS

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APPENDIX

The following SEM software was generally available in 2001. A comparative review of three of the most popular SEM programs (AMOS, EQS and LISREL) is provided by Kline (1998).

AMOS (Arbuckle, 1994, 1997) is a general-purpose SEM package (http://www.smallwaters.com/) also available as a component of SPSS statistical analysis software.

CALIS (Hartmann, 1992) is a procedure available with SAS statistical analysis software (http://www.sas.com/).

EQS (Bentler, 1989, 1995), is a well-known SEM package focussing on estimation with non-normal data (http://www.mvsoft.com/).

EzPath (Steiger, 1989) provides SEM capability for SYSTAT statistical analysis software (http://www.spssscience.com/systat/).

LISCOMP (Muthén, 1988) pioneered estimation for non-normal variables and is a predecessor of MPLUS.

LISREL (Jöreskog and Sörbom, 1993), with coupled modules PRELIS and SIMPLIS, is one of the oldest SEM software packages. It has been frequently upgraded to include alternative estimation methods and goodness-of-fit tests, as well as graphical interfaces (http://www.ssicentral.com/).

MPLUS (Muthén and Muthén, 1998) is a program suite for statistical analysis with latent variables that includes SEM (http://www.statmodel.com/index2.html).

Mx (Neale, 1997), a matrix algebra interpreter and numerical optimizer for SEM is available as freeware (http://views.vcu.edu/mx/).

SEPATH for STATISTICA software provides SEM with extensive Monte Carlo simulation facilities (http://www.statsoftinc.com/).

STREAMS (Structural Equation Modeling Made Simple) is a graphical model specification interface for AMOS, EQS, and LISREL (http://www.gamma.rug.nl).

TETRAD software (Scheines, et al. ,1994) also provides tools for developing SEM by generating input files for CALIS, EQS or LISREL (http://hss.cmu.edu/HTML/departments/philosophy/TETRAD/tetrad.html)