Indications and Limitations of Structural Equation Modeling in Complex Surveys: Implications for an Application in the Medical Expenditure Panel Survey (MEPS)

Janet L. Valluzzi, Sharon L. Larson, G. Edward Miller, Agency for Healthcare Research and Quality, Center for Financing, Access, and Cost Trends;
540 Gaither Road, Rockville, MD 20850

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Introduction

This paper examines some indications and limitations of structural equation modeling (SEM) in complex survey analysis using an example from the Medical Expenditure Panel Survey (MEPS). The primary objectives of this paper are: 1) to provide an overview of basic statistical issues related to SEM, 2) to discuss findings in the literature related to SEM and complex survey design, and 3) to discuss a substantive application of SEM to MEPS. MEPS data are used to develop a preliminary model of the relationship between parental reports of affective behaviors and psychotropic medication utilization for children aged 5-17. Findings are presented from a comparison of SEM analysis, which uses latent variables to model affective behaviors, to a regression analysis which uses indices which are created from observed variables to represent affective behavior. The paper concludes with a discussion of the findings from the two analytical approaches and discussion of next steps in model development.

Brief Overview of Structural Equation Modeling

This brief overview of SEM describes latent variables; model development and evaluation of fit; underlying analytical properties; and sample size considerations in the use of SEM. A key feature of SEM is its ability to link observed indicators to latent variables. Latent variables are hypothetical or unmeasured variables, which are free from random or systematic measurement errors and are observed only indirectly or imperfectly through their effects on observed or manifest variables (Bollen, 1989). Latent variables are utilized in situations where the constructs are not directly measurable, such as perception of pain or depression. Standard statistical procedures do not typically offer a convenient way to differentiate between observed and latent variables. SEM, however, provides a method of distinguishing between observed indicators and latent variables that accounts for the imperfect reliability and validity of measures (Kline, 1998). In SEM, both the observed indicators, and the errors associated with the measurement of the indicators, are identified in constructing latent variables.

Structural equation models are mathematical relationships representing the structure or hypothesized relationships among variables. SEM is an “a priori” technique in which theory drives the development and specification of the model, as opposed to mining the data to develop a model (Kline, 1998). The analysis focuses on the fit of the data to the theoretical model (Schumacker & Lomax, 1996). SEM also allows the analyst to make quantitative estimates of model parameters and to estimate goodness of fit. There is no single statistical test of significance that identifies a good fit of the data to the theoretical model. Instead, a wide variety of criteria can be computed to assess how well the data fit the model, including Chi-square, goodness-of-fit, and root-mean-square-error-of-approximation (RMSEA), which are three of the more commonly utilized criteria (Schumacker & Lomax, 1996). It is generally recommended that model fit criteria be used in combination with model comparison and model parsimony to assess whether or not the data for the population matches the “a priori” model (Schumacker & Lomax, 1996).

SEM’s underlying analytical processes differentiate it from both factor analysis and ordinary least squares (OLS) regression. SEM is not a single statistical technique, rather it is a family of analytic tools that utilize covariance matrices to address hypotheses about models. SEM uses a matrix of variances and covariances among observed variables to estimate latent variables. It differs from factor analysis, a set of procedures which primarily uses correlation matrices between variables to reduce or group the observed variables into a smaller number of factors (Munro, 2001). Estimates in SEM are often, but not always, derived using the maximum likelihood (ML) method, an estimation method that chooses the set of parameter values with the highest probability of generating the sample observations. Further, SEM differs from the OLS method, which obtains estimates of coefficients that minimizes the error sum of squares (Muthen, 1998).

SEM requires a large sample size, generally several hundred observations, as the precision of the estimates is affected by sample size (Schumacker & Lomax, 1996; Munro, 2001). The large sample size requirement for SEM can potentially be met through use of data from large national surveys, although the complex survey design of some national surveys raises other considerations, such as the need to consider sample clustering and stratification. The estimation strategies used in MEPS to account for the complex survey design and nonresponse have been previously published (Cohen et al, 1999). Failure to adequately address adjustments for clustering and stratification may bias standard error estimates and inflate chi-square values for larger SEM models (Muthen and Satorra, 1995).

Literature Search of SEM in Complex Surveys

A literature search of seventeen databases relating to science, social science, business, biological science, and pharmaceutical information was undertaken to determine whether or not any previously published articles had used SEM to analyze complex survey data. Literature search terms included the phrases SEM, national survey, population, and complex survey design. Forty studies that used SEM to analyze complex survey data were identified; however, none of these studies clearly documented adjustments for both clustering and stratification. For example, some studies utilized SEM with complex survey data, but did not mention weight adjustments or complex survey design (Farmer and Ferraro, 1997; Talbott and Thiede, 1999). Kirby (2002) specifically states that SEM estimates "cannot be adjusted for the complex sample design of the National Longitudinal Study of Adolescent Health" and notes that while sample weights are applied in all the analyses; adjustments for sample clustering were not made to SEM path analyses. Stump, et al, (1997) indicated that employing the complex sampling and post-stratification weights of the respondents in the 1993-1994 Asset and Health Dynamics (AHEAD) data for those aged 70 or more yielded similar results as analysis with unweighted data; however, weighted and unweighted estimates were not shown.

A key factor for the failure to make adjustments for the complex survey design in SEM may be that current SEM software makes it difficult to adjust for both components of the complex sample design: clustering and stratification. The "complex" feature of M-plus in the current preliminary investigation allows for adjustment for clustering within the sample design. However, M-plus currently limits the dependent variable in this feature to a continuous variable when making this design adjustment. Other SEM software, such as Lisrel, may allow for categorical or ordinal dependent variables but will not adjust for a complex sample. Currently available SEM software also limits 7estimators in complex survey analysis. For example, Mplus software limits the estimator to maximum likelihood estimates which provide parameter estimates with robust standard errors and mean adjusted (MLM) or mean and variance adjusted (MLMV) chi-square tests (Muthen and Muthen, 1998). Software such as SUDAAN and STATA address complex survey design, but do not necessarily perform SEM analyses. A summary table of selected software options currently available for SEM analysis in complex surveys follows.

Table 1: Summary Chart of Selected Software Options for Structural Equation Modeling (SEM) Analysis in Complex Surveys

	SEM	Weight	Cluster	Dependent Variable Restrictions
Mplus, v. 2[1]	✓	✓	✓	Continuous
Lisrel, v. 8.5 [2]	✓			Ordinal, Continous
Stata, v. 8, [3]		✓	✓	
Sudaan v.7.5, [4]		✓	✓	

Sources: 1. Muthen and Muthen, 1998, 2. Jöreskog and Sörbom, 2001, 3. McDowell, 2003, 4. Shah et al, 1997.

Research Strategy

In light of our literature search findings and the limitations of currently available software, we examine alternative methods of applying models with latent constructs to complex survey data. The specific application is a preliminary analysis of the relationship between psychotropic drug use by children, aged 5-17, and the latent constructs associated with their parent-reported affective behavior. This analysis uses data from the MEPS, which has a complex survey design that uses both stratification and clustering. Our primary goal is to use SEM to estimate latent constructs for children's affective behavior. We compare the SEM to a regression model which creates indices from observed variables to represent children's affective health behavior.

Data Sources

The MEPS is a nationally representative survey of the civilian, non-institutionalized population administered annually since 1996. The annual sample of households for the MEPS is a sub-sample of households that responded to the prior year's National Health Interview Survey (NHIS). MEPS is designed to produce national estimates of health care expenditures, insurance coverage, and sources of payment for health care. The detailed information collected in the MEPS Household Component (MEPS HC) can also be used for behavioral studies related to insurance coverage, the cost of health care, and access to health care.

The MEPS prescription medication (PMED) files provide information about pharmaceutical utilization and expenditures and include the identifying National Drug Codes (NDC) and related medical conditions. For this study, each drug in the MEPS PMED files was assigned to a therapeutic class and subclass by using the NDC to link the PMED files to the Multum Lexicon, a product of Cerner Multum, Inc. The Multum Lexicon is an electronic dictionary that provides comprehensive drug and disease information. Additional information about the MEPS and Multum Lexicon data can be found at their respective websites: http://www.meps.ahrq.gov and www.multum.com.

Identification of the Sample for Data Analysis

This study uses data from the MEPS HC for the years 1996-1999. The MEPS HC uses an overlapping panel design, with 5 rounds of data collected for each panel over a two year period. The unit of analysis in this study is the person-year. That is, health care use and expenditures for each child are summed, and are analyzed, within a calendar year. For children aged 5-17, the combined four years of MEPS HC data yield a total of 22,211 person-years and 45,242 drug purchases.

For this study, children were identified as having psychotropic drug use if they used at least one drug that was classified as a psychotropic drug in the Multum Lexicon, and if the condition reported by the household respondent as associated with the psychotropic drug use was related to mental health or substance abuse. Psychotropic drugs are prescribed for various brain disorders, such as depression, attention deficit hyperactivity disorder (ADHD), and bipolar disorders. They may also be prescribed for some conditions unrelated to mental health or substance abuse, such as epilepsy. The strategy of only including reported psychotropic drug use for which there was an associated mental health or substance abuse condition is consistent with previous research on psychotropic drug use and expenditures by Zuvekas (2001).

Table 2 provides information on MEPS' sample sizes for each year from 1996-1999, including the unweighted and weighted number of children aged 5-17, and the weighted number and percentage of children aged 5-17 that have psychotropic drug use during each year of analysis. In each year from 1996-1999, the estimated total population of children aged 5-17 in the United States ranged from 51.7 to 53.1 million, and the estimated percentage of children using psychotropic drugs each year ranged from 3.8 to 4.7 percent. No significant differences were found between years in the percentage of children using psychotropic drugs; therefore, we felt comfortable combining years of data. The mean annual use ranged from 0.28 to 0.34 prescriptions per year and increased each year.

Table 2: MEPS Sample Characteristics (1996-1999): Children, Aged 5-17[1]

Children, Aged 5-17	1996	1997	1998	1999
Unweighted Sample	4,621	7,302	5,175	5,113
Total Population (millions)	51.68	52.39	53.06	52.93
Total With Psychotropic Drug Use (millions)	1.94	2.35	2.49	2.31
Percent With Psychotropic Drug Use	3.75% (0.38)[2]	4.48% (0.32)	4.69% (0.38)	4.36% (0.37)
Mean Annual Use	0.28 (0.04)[2]	0.31 (0.03)	0.33 (0.04)	0.34 (0.04)

1. Source: authors' calculations from the 1996-1999 MEPS HC. 2. Standard errors identified in parentheses.

Constructs of Interest from the Literature Related to Psychotropic Drug Use

As noted, the primary goal of our analysis is to examine an application of SEM in complex survey data. To do this, we initially developed a SEM model (Figure 1) that addressed our substantive research question: what constructs are predictive of the number of prescriptions for psychotropic drugs for children aged 5-17? Previous research provides some insight into socioeconomic (SES) characteristics that would potentially contribute to a model of children's use of psychotropic drugs. These selected SES characteristics include race/ethnicity

(Chow et al, 2003; Rowland et al, 2002); special education status (Safer and Malever, 2000); age and gender (Martin, 1999; Rowland et al, 2002); co-morbidity (Brown et al, 200; Safer et al, 2003; Woolston, 1999); and geographic location (Cox et al, 2003). The source of payment for health care is identified in the literature as a key treatment factor for psychotropic drug use (Zito et al, 2003). These findings in the literature helped shape the SES characteristics included in our "a priori" model.

Variables of Interest

We identified SES variables of interest from MEPS relating to race/ethnicity; special education participation; income; geographic region of residence; insurance status; residence in metropolitan or non-metropolitan area; and age. Based on findings in the literature, we dichotomized some of these variables to simplify our analysis in the preliminary model. For example, since the prevalence of psychotropic use in children was identified as being higher in the south, we dichotomized our variable to yes = residence in the south; and no = residence elsewhere.

Published prevalence data from the literature also indicated that two to three times more children were receiving psychotropic medication of all types in 1996 than in 1987 (Zito et al, 2003; Jellinek, 2003). This increase is attributed to a myriad of scientific, clinical, financial, and systems changes (Jellinek, 2003). For example, managed care cost controls that were applied to general pediatric care and child mental health services during that time frame may have provided incentives for increased medication use instead of behavioral therapies or combined medication and behavioral therapy approaches to treatment (Jellinek, 2003). The increased use of medication therapies to treat children highlighted the need for additional model components that examines latent determinants of psychotropic drug use among children.

Therefore, our preliminary model also addresses the association between children's affective behaviors, as reported by their parents, and children's use of psychotropic drugs. In our analysis we use parent reports of behavior. On the surface this appears to be a directly observable set of behaviors rather than a set of latent constructs. For example, is a child is not getting along with siblings, parents can tell us that this is occurring from their own observation. We suggest that what is latent is the underlying meaningfulness of these behaviors. For example, if a child is having relationship problems with parents, siblings and friends, the behavior is not necessarily the important characteristic. Rather, what is causing the behavior is the important consideration. While we cannot pinpoint the cause of the behavior with our data, we can suggest that there is either a system (family) or psychiatric condition that is reflected in the behavior of the child as reported by the parent. So, our interest is not really about the behaviors specifically, but about what underlying trait may have caused the reported behaviors. We use the terminology "affective behaviors" to indicate that these are measures of reported observations of behaviors instead of measures of behavior itself. Thus we use the behavioral reports as our best indicators of some underlying, or latent, state or trait that is associated with psychotropic drug use.

Methods

Researchers have employed a number of approaches to address latent constructs. One frequently used approach is the construction of an index from several variables intended to reflect an underlying latent construct. Two statistical analyses are commonly used to examine the qualities of the items used in these indices. First, researchers may explore the structure of the items posited to represent a latent construct using Exploratory Factor Analysis (EFA). EFA suggests a relationship between the individual items and factors. A strong association between an item and a factor, a large factor load, suggests that the item covaries with the factor. If the items that load on a particular factor appear to be substantively similar and could reasonably be considered to represent a particular domain, the researcher may use this index to represent a particular latent construct.

A second type of analysis is to examine the internal reliability of the items used to construct an index. The higher the correlation is between items within the index, the greater the likelihood that they are measuring the same construct. Intercorrelation between items is measured using Cronbach's alpha, an internal reliability measure which ranges from zero (no internal consistency) to one (perfect consistency). An overall alpha reliability of .70 or higher is typically considered sufficient to justify using a set of variables to construct an index.

In our study we conducted both of these procedures to create indices utilized in the OLS regression analysis. Our preliminary examination of MEPS data identified thirteen ordinal affective behavior items that were developed from survey response by parents for children, aged 5–17. Using EFA, we grouped these observed affective behavior variables to create three indices to represent underlying characteristics of children's affective behavior. (See Figure 1).

The three latent constructs identified in our EFA analysis were: 1) Affective relationships: problems with behavior at home, including getting along with mom, dad, and/or siblings; 2) School issues: school related affective behavioral problems; and 3) Experiences: community participation affective behavior variables such as having problems interacting with adults, other children, or participating in sports and affective behavior characteristics such as being unhappy, nervous or afraid. Alpha reliability tests provided information on how the items were correlated. The respective Chronbach's alpha for each of these indices was: affective relationships, 0.83; school issues, 0.81; and experiences, 0.83. The reliability tests also showed that none of the 13 items should be deleted to improve the reliability of these constructs.

We also construct a similar set of latent constructs using SEM. In the SEM approach, factor loadings are interpreted as regression coefficients that estimate the direct effect of a particular factor on the items thought to be indicators of the factor. In this approach the model accounts for the common variation within the items that is represented by the factor and additionally accounts for unique variation that may be unrelated to the factor. SEM accounts for the measurement error associated with using items that imperfectly measure a particular construct. Thus, in a SEM approach we gain an increased understanding about how the item loads on the factor, how much unexplained or unique variation remains, and finally, with model fit measures it is possible to consider how well the data fit the hypothesized model.

To estimate our SEM model we regressed the number of psychotropic drug purchases per child per year on our three latent variable constructs and the SES characteristics of interest as identified in the literature. Using Mplus software, we were able to weight and adjust for primary sampling unit (psu) clusters. We then applied a similar approach in an OLS regression model using STATA software. We regressed the number of psychotropic drug purchases per child per year on the three created indices of parent-reported affective behavior and the SES variables of interest. The STATA regression adjusted for stratification, clustering, and weighting to account for the MEPS complex survey design. A comparison of findings from both approaches is listed in Table 3.

Table 3: Comparison of SEM and Regression Estimates

	SEM		**Regression**	
Variable	**Estimate**	**SE[1]**	**Estimate**	**SE**
SES				
Race/ Ethnicity White	0.24	0.04	0.24	0.04
Spec Ed Part.	1.40	0.13	1.38	0.18
Income	-0.00	0.02	-0.01	0.02
Region South	0.05	0.03	0.05	0.04
Uninsured	-0.16	0.03	-0.16	0.04
Metro	-0.03	0.04	-0.03	0.07
Age Group	-0.05	0.01	-0.06	0.02
Affective Behavior				
Affective Relationships	0.03	0.06	0.07	0.03
School Issues	0.23	0.08	0.16	0.04
Experiences	0.28	0.07	0.18	0.05
$\mathbf{R^2}$	0.09		0.07	

Source: Authors' calculations from the 1996-1999 MEPS HC. 1. SE: standard error.

Results

Table 3 presents a comparison of our SEM and regression analysis estimates. The top half of Table 3 shows that the magnitudes and signs of the coefficients for the SES variables, which are directly observed and recorded in the MEPS data, are very consistent across the two models. For example, participation in special education programs is associated with an increase of 1.40 psychotropic prescriptions per year in the SEM model and is associated with an increase of 1.38 prescriptions per year in the regression model. Being uninsured, on the other hand, is associated with a decrease of -0.16 prescriptions per year in both models. Another pattern which is evident in the SES variables is that the standard errors are slightly larger in the regression model than in the SEM model. It is not surprising that point estimates in this portion of the analysis were equivalent since the variables of interest were observable and represented the exact same construct in each analysis. It is likely that adjustments for the complex survey account for the differences in standard errors.

Interesting differences did however emerge in the analysis of the affective measures of behavior. Recall that in the regression analysis three measures were constructed to serve as concrete measures of behavior. These measures are summed indices of three domains of children's affective behavior as reported by parents. The creation of these measures does not account for the magnitude of contribution each variable makes to the overall construct, rather, all items are assumed to contribute the same to the construct. For example, in the index labeled "affective relationship", any problem with the relationship with mother is assumed to be equivalent to a problem with sibling(s). Further, this process of creating and using summed indices does not account for other factors that may contribute to a particular response on an individual item. The regression analysis reveals that all of the affective behavior indices are significantly associated with number of psychotropic prescriptions. For each one point increase in the affective relationship index there is a .07 increase in the number of psychotropic prescriptions filled. Likewise, for each one point increase in school issues or experiences, there is a .23 and .28 increase respectively, in the number of prescriptions filled for psychotropic medications.

The SEM analysis reveals somewhat different findings. Recall that the SEM analysis is able to account for both the common variance associated with each factor, allows different variables to have different magnitudes of contribution to the latent construct, and reflects the variance that is not accounted for by each factor. The SEM analysis suggests that only school issues and experiences are significant. Each one point increase in school issues is associated with a .23 increase in number of psychotropic prescriptions filled, while each one point increase experiences is associated with a .28 increase in number of psychotropic prescriptions.

The lack of significance associated with the affective relationships factor will require further investigation. The difference between the SEM and regression approach suggests that there may be other items which should be included in this measure, or that factors other than affective relationships explain the responses to the items associated with these factors. For example, a response indicating problems with mother may actually be related to the gender of the parent reporting the problem, an interaction between child gender and parent gender, or gender role expectations within society. Further, items may vary in the magnitude of their relationship to the factor under investigation in SEM and this may lead to differences in the point estimates and standard errors.

In general, it appears that SEM may be a viable and valuable set of analytic tools for evaluating complex survey data. Point estimates are comparable despite the inability to fully adjust for the complex sample design. However, standard errors continue to require investigation. The standard errors for the observable measures were similar in most instances. Differences that emerged in the examination of the behavioral measures appeared to be unrelated to the complex survey design and are more likely the result of differences in the method of constructing unobserved or latent variables.

In light of these findings, we conclude that SEM more completely addresses latent variables because it can account for the underlying latent constructs that are observable, but not measured directly, such as parent-reported children' affective behaviors. However, while Mplus SEM software allows adjustment for weighting and clustering, it will not adjust for strata, thus the full application of SEM is not yet available for complex survey analysis. For example, SEM fit indices that assess the omnibus model fit, i.e. the Root Mean Square Error of Approximation of 0.069 in our preliminary SEM model, but it does not consider both clustering and stratification. Also, use of current SEM Mplus software restricted our analysis to a continuous dependent variable of number of psychotropic drug events when making adjustments for complex survey design.

Summary and Next Steps

In summary, this paper presented a preliminary application, designed primarily to examine SEM methodology, in a complex survey. Since we did not find any examples in the literature of analyses of complex survey data using SEM models that make appropriate adjustments for weights, clustering, and stratification, we compared our SEM estimates using latent variables to a regression model using indices of observed variables to identify parent-reported affective behaviors and selected SES variables associated with the number of psychotropic medications used. We found that the magnitudes and signs of the coefficients for the SES variables, which are directly observed and recorded in the MEPS data, are very consistent across the two models. Standard errors are slightly larger in the regression model than in the SEM model, most likely due to differences in software adjustment for the complex survey design. Differences did emerge between the two approaches in measures of affective behavior. The regression analysis revealed that all of the observed indices of parent-reported affective behavior are significantly associated with number of psychotropic prescriptions; however, the SEM analysis suggests that only two of the latent constructs, school issues and experiences, are significantly associated with the number of psychotropic prescriptions. The difference between the SEM and regression approach suggests that there may be other items which should be included in this measure, or that characteristics other than affective relationships explain the responses to the items associated with these characteristics.

Future methodological research will include examination of the direct effects of observed variables on expenditures and distributional qualities of data and the use of categorical dependent variables in SEM with complex surveys when software is available. In addition, we anticipate a review of the clinical criteria for the selected sub-population of interest, as the criteria currently used for inclusion of those children with psychotropic drug use are changing with different evidence regarding etiology and clinical practice. Finally, other constructs or variables of interest for further model development include: additional examination of observed variables of affective behaviors; development of the latent concept of burden; examination of the effects of co-morbidity on psychotropic drug use and expenditures, and analysis of the influence of child and/or parent gender. Starting in the year 2000, the MEPS introduced a parent questionnaire which measures health status that may provide additional model parameters for analysis.

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Figure 1: Preliminary Model